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Integrated network flow model for a reliability assessment of the national electric energy system

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Integrated network flow model for a reliability assessment of the national electric energy system

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Abstract

Electric energy availability and price depend not only on the electric generation and transmission facilities, but also on the infrastructure associated to the production, transportation, and storage of coal and natural gas. As the U.S. energy system has grown more complex and interdependent, failure or degradation on the performance of one or more of its components may possibly result in more severe consequences in the overall system performance. The effects of a contingency in one or more facilities may propagate and affect the operation, in terms of availability and energy price, of other facilities in the energy grid. In this dissertation, a novel approach for analyzing the different energy sub-systems in an integrated analytical framework is presented, by using a simplified representation of the energy infrastructure structured as an integrated, generalized, multi-period network flow model. The model is capable of simulating the energy system operation in terms of bulk energy movements between the different facilities and prices at different locations under different scenarios. Assessment of reliability and congestion in the grid is performed through the introduction and development of nodal price-based metrics, which prove to be especially valuable for the assessment of conditions related to changes in the capacity of one or more of the facilities. Nodal price-based metrics are developed with the specific objectives of evaluating the impact of disruptions and of assessing capacity expansion projects. These metrics are supported by studying the relationship between nodal prices and congestion using duality theory. Techniques aimed at identifying system vulnerabilities and conditions that may significantly impact availability and price of electrical energy are also developed. The techniques introduced and developed through this work are tested using 2005 data, and special effort is devoted to the modeling and study of the effects of hurricanes Katrina and Rita in the energy system. In summary, this research is a step forward in the direction of an integrated analysis of the electric subsystem and the fossil fuel production and transportation networks, by presenting a set of tools for a more comprehensive assessment of congestion, reliability, and the effects of disruptions in the U.S. energy grid.

1 Introduction

1.1 Motivation

The President's Commission on Critical Infrastructure Protection [PCCIP, 1997] has identified electric power as a critical infrastructure sector. But the economic and physical integrity of the electric energy system in the US depends not only on the integrity of the electric grid but also on the ability to produce, transport, and transform into electric energy the various forms of primary energy. According to 2005 data, these primary energy forms include fossil fuels (i.e. coal, natural gas, and petroleum), which were responsible for almost 70% of the national electric energy supply, with most of the remainder being nuclear and hydroelectric energy, and a smaller percentage being renewable sources (wind, solar, etc.). Figure 1.1 shows the shares of electric net generation for 2005 [EIA, 2006a].

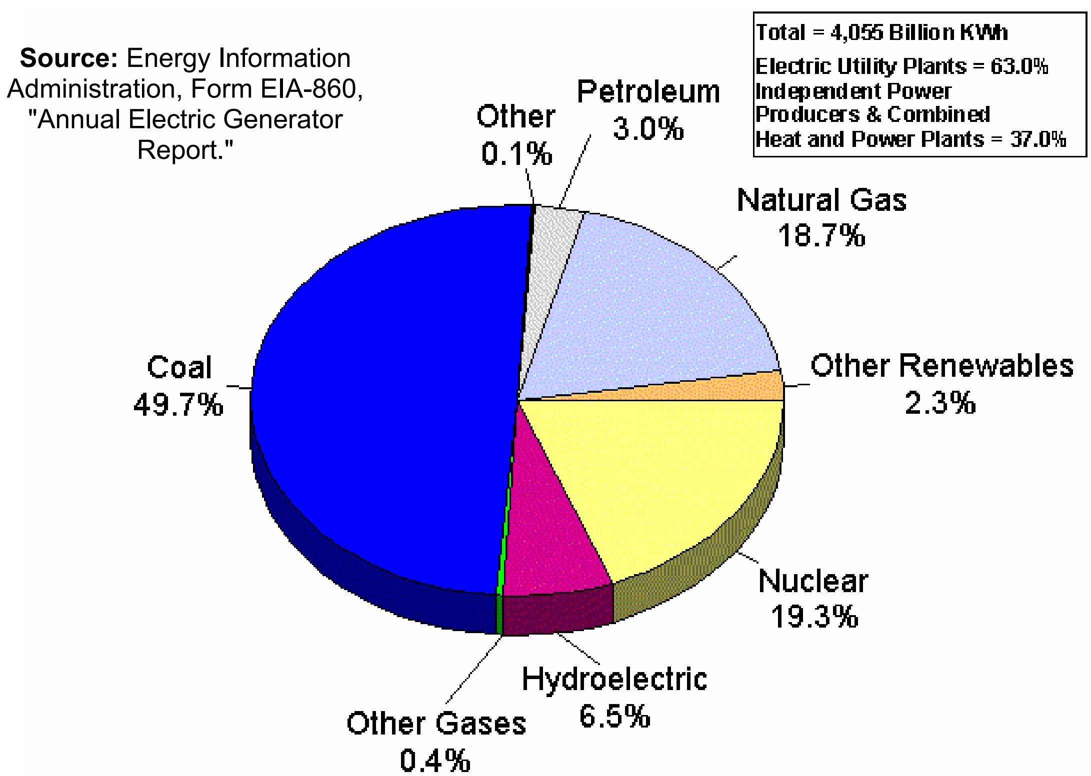


Figure 1.1. U.S. Electric Power Industry Net Generation, 2005 [EIA, 2006a]

As the U.S. energy system has grown more complex and interdependent, failure or degradation on the performance of one or more of its components may possibly result in more severe consequences in the overall system performance. These consequences might permeate and affect the national economy and might also raise national security issues. In addition, increasing competition brought by deregulation within the energy industry has forced facility owners to use their existing resources more efficiently, that is, closer to their operating limits. Congestion occurs when a binding limit on the system's transfer capability is reached, and leads to price increases as less economic paths are needed to transport the energy where it is finally consumed. In the energy industry, increasing congestion has raised concerns about the system ability to tolerate disruptions to one or more of its facilities and the effects that contingencies might have in energy prices.

Figure 1.2 illustrates the relationship between disruptions and prices. The curve shows the costs of natural gas to electric utilities since 2000, and has two pretty obvious peaks in the first months of 2001 and in the last months of 2005. These peaks are directly associated to disruptions in the system facilities: the natural gas pipeline explosion in El Paso in 2001 and the Katrina and Rita hurricanes in the Gulf Coast in 2005, which affected natural gas production and transportation. Since the cost of natural gas for electric power increased as a direct result of the congestion caused by these disruptions, the price of electric energy also increased. With natural gas being more expensive at the time these disruptions took place, the shares of coal and natural gas use for electric generation were also modified. Hence, the effects of these disruptive events in the natural gas subsystem permeated to the electric and coal subsystems, being price the most important link through which the interdependencies between subsystems took place. This connection between capacity, reliability, and prices motivates us to develop a model able to simulate how both energy flows and energy prices will behave in different geographic locations in the aftermath of a disruptive event.

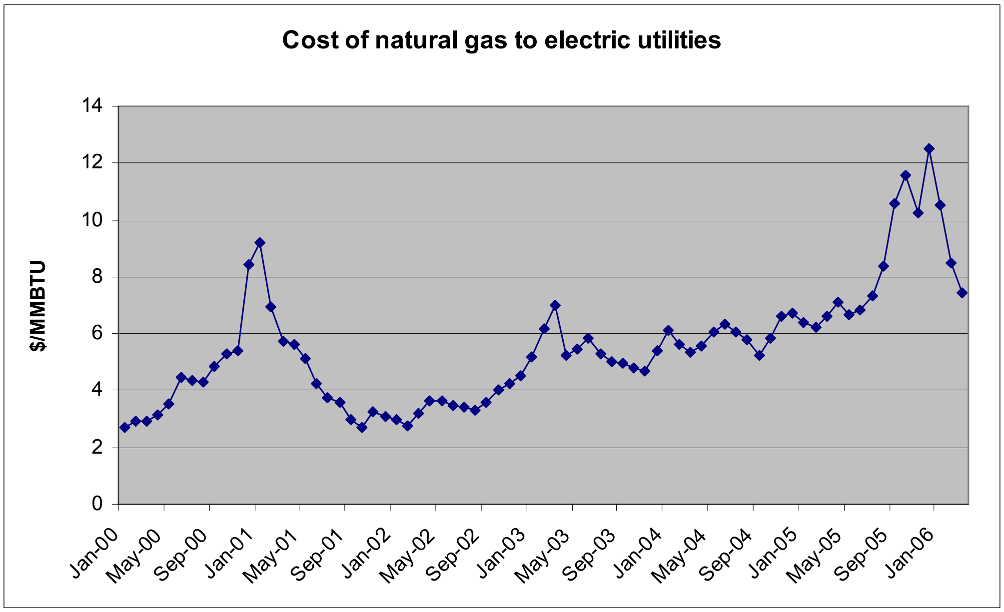


Figure 1.2. Cost of NG to electric utilities 2000-2006

Although economic and physical performance of individual energy subsystems has been well studied and understood there has been little effort to study its global characteristics. This has been partly due to the difficulty in formulating models capable of analyzing the integrated system while accounting for characteristics unique to each subsystem. As it was previously mentioned, given the increasing interdependencies in the energy infrastructure, the effects of a contingency in one energy subsystem may propagate and affect the operation, in terms of availability and price of energy, of a different subsystem. The current research study intends to take a step forward in the direction of an integrated analysis of the electric subsystem and the fossil fuel production and transportation networks.

Analysis of reliability and prices in the U.S. energy system may serve different purposes: 1. to evaluate the severity of conditions that might be harmful to the systems, 2. to discover where the system is more vulnerable, and 3. to recognize where capacity expansion investment should be located. Furthermore, an integrated analysis of the NEES will provide a better understanding of how the interdependencies in the system work, shed some light on how reliability and price are linked, facilitate the identification of alternative energy supplies, and be of assistance in the prevention of resource adequacy problems.

1.2 The National Electric Energy System

The National Electric Energy System (**NEES**) in this work is understood as the integrated infrastructure associated to the production, transportation, storage (where applicable), generation, and end-use of electricity, natural gas, and coal, as illustrated in Figure 1.3.

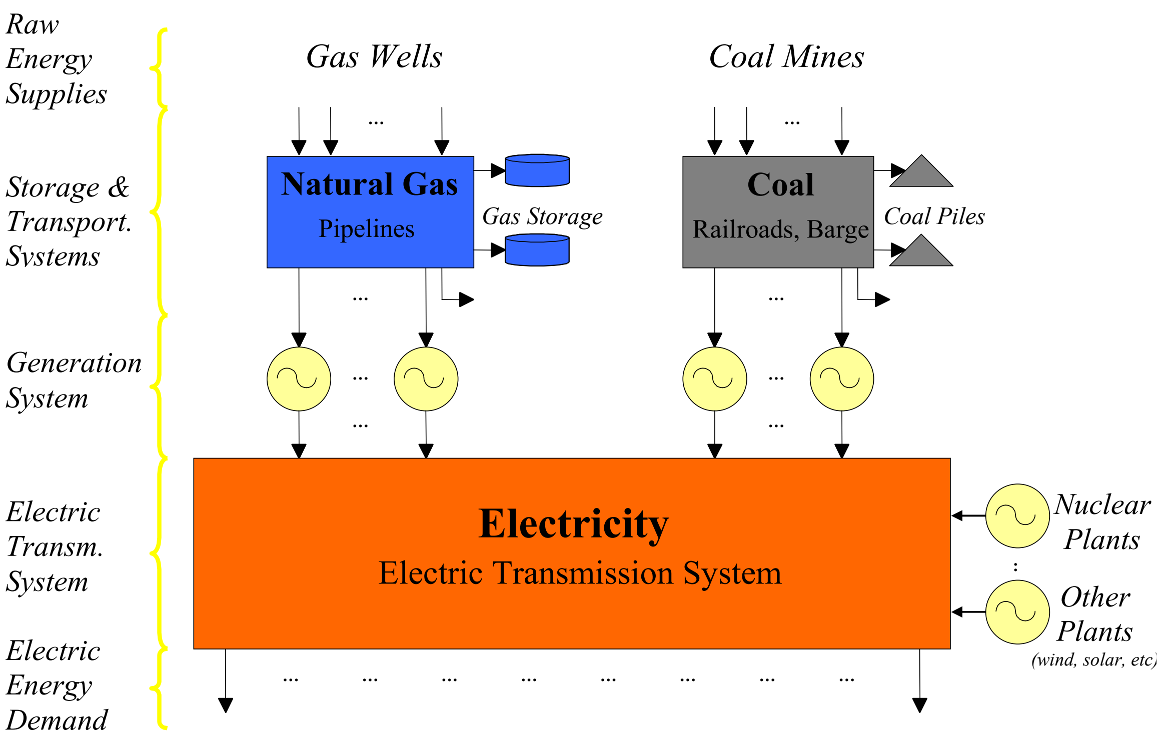


Figure 1.3. National Electric Energy System (NEES)

Coal and natural gas share the common characteristic that they are moved via a transportation network from their source of production (coal mines and gas wells) to the generation plants where they are converted into electric energy. Coal is mainly moved by train, barge, and truck, while natural gas is moved by pipelines. Coal and natural gas also share the capability for being stored: coal in stockpiles usually close to the coal-fired power plants and natural gas in depleted natural gas and oil fields, aquifers, and salt caverns. After the fossil fuels have been converted into electric energy in the generation plants, electric energy is supplied to the consumers through the transmission grid.

1.3 Objectives

The implicit hypothesis of this work is that by analyzing the different energy sub-systems in an integrated analytical framework, we will be able to perform a better assessment of the reliability and the effects of disruptions in the NEES than by analyzing the systems separately. Such integrated analytical framework, along with the techniques derived from it, will allow the decision makers to firstly, elaborate preventive and corrective plans to avoid energy shortages and secondly, dampen the negative effects that catastrophic contingencies may have in the energy supply. More specifically, the main objectives of this work are to:

1) Build an operational model of the NEES, capable of simulating NEES operation in terms of bulk energy movements between the different facilities and prices at different locations under different scenarios.

2) Introduce the concept of reliability in the context of the NEES model, and develop the theoretical framework that supports it by studying the relationship between prices, congestion, and reliability.

3) Develop techniques aimed at identifying system vulnerabilities and conditions that may significantly impact availability and price of electrical energy.

4) Assess the impact of disruptions in the performance of the NEES by creating metrics based on transportation capacity and price of energy at different locations.

5) Create metrics to evaluate capacity expansion decisions from an economical as well as a reliability point of view.

To achieve these goals, a network flow model for reliability assessment of the NEES will be introduced. In this model, the electricity, coal, and natural gas subsystems are analyzed together in a single integrated mathematical framework for the primary energy production, transportation, and storage, and for the electric energy generation and bulk transmission. It is expected that such model might prove effective in enhancing national economic competitiveness and securing the energy supply by establishing a framework for making decisions in the context of the NEES.

1.4 Literature Review

A number of papers in fuel scheduling that deal with the optimization of electric energy production have been published throughout the years [Wood & Wollenberg, 1996], [Vermuru & Lemonidis, 1990], [Vickers et al., 1994], [Djukanovic et al., 1996], [Shih & Frey, 1993], [Rosenberg et al., 1990], [Moslehi et al., 1991], and [Wong & Wong, 1997]. We note, however, that all known approaches have seen the fuel system as exogenously given, i.e., there has been little effort to optimize fuel production, storage, and transportation together with electric generation and transmission, a gap the current work attempts to bridge.

For coal transportation, a number of optimization models can be found in the literature. Some of the earlier ones include [Morlok & Peterson, 1970] and [Bernknopf, 1985] Later models as the ones introduced by [Elmes, 1984], [Chang et al., 1981] include additional refinements. More recent models as the one proposed in [Pendharkar, 1997], is a generalized fuzzy linear programming model for solving the coal production scheduling problem. A theory for modeling and optimizing power plant coal inventories is presented in [Merril, 1988].

Several other papers have addressed the natural gas well production optimization as in [Bitsindou & Kelkar, 1999] and more recently [Edwards, 2002]. Linear and nonlinear techniques are used and described in [Linden et al., 1999] and [Siregar et al., 2000] the optimization of a pipeline network in terms of the pipe diameter and routing is addressed using linear programming and dynamic programming. While the simple structure of a network formulation cannot accurately capture the non-convexities describing the feasible set of values and costs of transporting gas through the pipeline network, more general formulations are available and have proven useful in appropriate contexts [Swoveland & Lydiatt, 1993]. The effects of non-smooth and discontinuous behaviors are addressed by [Carter et al., 1993]. Research has also been done in hydrothermal generation scheduling, that is, the optimization of electric energy production together with the optimal use of water resources. Different approaches can be found in the literature to solve this problem [El-Hawary, 1990], including Lagrangian relaxation [Johnson et al., 1998], [Al-Agtash & Su, 1998], and [Ruzic & Rajakovic, 1998]; network linear programming [Johannesen et al., 1991]; mixed-integer programming [Tufegdzic et al., 1996]; neural networks [Liang & Hsu, 1996]; tabu search [Bai & Shahidehpour, 1996]; Bender's decomposition [Pereira & Pinto, 1983]; and genetic algorithms [Gil et al., 2003a], [Onate & Ramirez, 2005], and [Ramirez & Oñate, 2006]. A major difference between the above cited literature and the approach presented in this research work is that we intend to design, develop, and study an integrated, interdependent energy system model that combines coal, natural gas, and electricity. In order to do this, a network model of the NEES is developed. Other attempts to incorporate different subsystems into an integrated framework (mostly electricity and natural gas) can be found in [Bakken et al., 1999], [An et al., 2003], [Soderman & Petterson, 2005], [De Mello & Ohishi, 2005] [Geidl & Andersson, 2005a], and [Geidl & Andersson, 2005b]. However, these approaches are mostly theoretically-oriented and have not explored its application in a real system of such a large scale as we are attempting to do it in this work.

Excellent references on network modeling and solution algorithms include [Glover et al., 1992], [Chvatal, 1980], [Balakrishnan, 1995], [Potts and Oliver, 1972], [Eiselt & Sandblom, 2000], and [Bixby, 2002].

On the area of network reliability, most of the literature deals with the estimation of performance measures related to the connectedness of networks, such as two-terminal reliability, source-to-all-terminal reliability, and source-to-k-terminal reliability, among others [Barlow & Proshan, 1975], [Harms, 1995], [Ionescu, 1999], [Lindqvist, 2003], [Meeker & Escobar, 1998], [Misra, 1993], [Ramakumar, 1993], and [Shier, 1991]. This type of reliability measure is especially useful for logic diagrams (protection systems, for example) or in communication networks where the capacities of the arcs are not that relevant. In contrast, in networks where the capacity, the costs, and the efficiencies of the arcs are important (as in this case), measures related to the connectedness of the network are not that significant.

On the field area of vulnerability identification in networks, a promising related concept is what in military applications is called network interdiction. Network interdiction consists of attacking an adversary's network with the objective of minimizing the network functionality using limited resources [Wood, 1993], [Israeli & Wood, 2002], [Cormican et al., 1998]. The same idea can be used with the opposite objective in mind, that is, defending critical infrastructure [Brown et al., 2005]. A network interdiction technique that seems to be particularly appropriate for identification of system vulnerabilities is the enumeration of near minimum minimal cut-sets presented in [Balcioglu, 2000] and [Balcioglu & Wood, 2003], a technique explored and expanded in the current work.

1.5 Thesis organization

This thesis is organized and presented through eight chapters. Chapter 1, *Introduction*, describes the motivation behind this work along with the objectives and organization. It also presents the theoretical review highlighting work relevant to the topic explored and researched in this work. Chapter 2, *Integrated Network Flow Model of the NEES*, provides the fundamental definitions and assumptions necessary to formulate and implement a network flow model of the NEES. In Chapter 3, *Improvements to the basic model for the study of disruptions*, some necessary adaptations to the basic model for the effects of simulating large disruptive events are introduced. Chapter 4, *Mathematical formulation and analytical framework*, presents the mathematical formulation underlying the NEES network model. Using some relevant results in duality theory, this chapter also discusses how changes in some of the network parameters affect the solution of the mathematical problem. Chapter 5, *Reliability in the NEES*, discusses the relationship between reliability, congestion, and nodal prices in the context of the

NEES. Also presented in this chapter are the main results and conclusions of a data gathering effort to evaluate the effects of hurricanes Katrina and Rita in the facilities of the NEES. Chapter 6, *Methodology*, introduces different metrics that can be obtained from the results of simulation on the NEES network model. These metrics will be later used for identification of system vulnerabilities, for evaluation of the effects of disruptions in the NEES, and for capacity expansion assessment. Chapter 7, *Numerical results*, presents numerical results related to the model validation and to the use of different metrics to evaluate the impact of a contingency and to evaluate capacity expansions. Finally, concluding remarks and directions for future work follow in Chapter 8.

2 Integrated Network Flow Model of the NEES

The U.S. electric energy system integrity depends not only on the electric generation and transmission subsystems but also on the ability to produce and transport the various forms of raw energy used to generate electric energy. Because of the existence of strong interdependencies between different energy sub-systems, the use of an integrated model that analyzes the operation of the NEES and the movements of energy in the transportation network will provide the decision makers with a better understanding of the interdependencies in the system.

A large number of practical optimization problems can be modeled as flows circulating through a structure formed by elements called nodes (sometimes called vertices) and arcs (sometimes called links or edges). Electrical grids, highway systems, manufacturing processes, communication networks, and hydraulic systems are some examples of real systems where a network-type model deems appropriately. Problems derived from these real systems, such as discovering the shortest-path, maximizing the flow in the network, or finding the minimum cost flow can be solved efficiently by using a network-flow approach. Since the energy system can be represented adequately by arcs and nodes and the bulk energy movements can be effectively characterized as flows, a network flow structure lends itself nicely to the characteristics of the problem. Moreover, a network flow model also allows representation of capacities, costs, and efficiencies of the different transportation modes. Furthermore, the use of network flows for modeling the NEES will also allow taking advantage of a well-developed graph theory and existent network flow optimization algorithms.

This chapter is organized as follows: Section 2.1, *Model description, definitions, and assumptions*, presents some basic definitions and assumptions needed to formulate the NEES network flow model. Some of its main features are also described in this section. Section 2.2, *Model implementation in the U.S. energy system*, presents how the theoretical model brackets together with the real US energy grid, by explaining what the actual facilities are or what set of facilities the nodes and arcs in the network represent. This explanation is achieved by discussing the level of data aggregation (determined mainly by data availability), and by indicating the main sources of the data used to set up the parameters associated to nodes and arcs. Section 2.3, *NEES network model implementation*, briefly introduces the practical implementation of the NEES network flow model using 2005 data that was used in the analyses to be presented in further chapters.

2.1 Model description, definitions, and assumptions

As mentioned previously, the NEES can be modeled using a generalized network flow structure. Such a structure lends itself nicely to many of the system constraints, such as conservation of energy and limited capacity of different facilities. A network structure allows the use of a well developed network theory for analyzing many different aspects that are of interest in studying the reliability and performance of the energy system, as it will be presented in following chapters.

2.1.1 Nodes

Nodes will be used to represent a point in the system where conservation of flow is enforced. Examples of such points are raw energy production and storage facilities, and electric power consumption locations. For the coal subsystem the nodes may represent production facilities (coal mines), storage facilities (coal piles), and coal-based thermal power plants. For the natural gas subsystem, the nodes represent production facilities (gas wells), storage facilities (depleted natural gas and oil fields, aquifers, and salt caverns), and gas-fired power plants. For the electric subsystem, the nodes represent electric power plants and electric consumption.

In theory, nodes can represent individual facilities of the system, but due mainly to the unavailability of detailed data, nodes will represent aggregated groups of facilities that share a similar functionality, certain homogeneity in their characteristics, and are located geographically close to each other. Facilities having a capacity associated to them can be modeled by using two nodes and a capacitated arc connecting them. In general, we can recognize the following types of nodes in terms of their functionality:

- Production nodes: Production nodes in the coal and natural gas subsystem represent aggregation of coal mines and gas wells respectively. In the coal subsystem, production nodes are connected by an outgoing arc to the corresponding storage and electric generation nodes located in their region. In the natural gas subsystem, production nodes are connected by an outgoing arc to the transshipment node corresponding to their region.

- Storage nodes: Storage nodes in the coal and natural gas subsystem may represent aggregation of coal piles and underground natural gas storage respectively. Storage nodes are connected by an inbound arc to the production nodes corresponding to their region and by an outgoing arc to their corresponding electric generation nodes. A storage node will be also connected to the same storage node but in a consecutive time step, as storage constitutes the link between different periods of time.

- Electric generation nodes: Electric generation nodes act as the link between the primary energy subsystems (coal and natural gas) and the electric subsystem. These nodes represent aggregation of electricity generation facilities sharing a similar location, type of fuel, and technology. Electric generation nodes are connected by inbound arcs to their corresponding production and/or natural gas transshipment nodes, and by an outgoing arc to the electric transshipment node corresponding to their region.

- Transshipment nodes: Transshipment nodes are used to represent final consumption of energy and to better model the actual energy movements in the NEES. Two types of transshipment nodes are defined: electric transshipment and natural gas transshipment nodes. Electric transshipment nodes are connected by inbound arcs to the electric generation nodes corresponding to their regions and by bidirectional arcs to the neighboring electric transshipment nodes. Natural gas transshipment nodes are connected by incoming arcs to the natural gas production nodes, by bidirectional arcs to natural gas storage nodes, by bidirectional arcs to other natural gas transshipment nodes, and by outgoing arcs to natural gas generation nodes.

2.1.2 Arcs

Arcs will be used to represent facilities where the flow has a limited capacity and/or where it has costs or losses associated. This includes, but it is not restricted to, transportation routes and associated transportation modes between the different nodes. In the coal subsystem, the transportation modes modeled include barges, railroads, trucks, pipelines, and multimodal. In the natural gas subsystem, the arcs represent gas pipelines. In the electric subsystem, the arcs represent transmission lines and the connections between the generators and the transmission system. As with the nodes, arcs can represent actual transportation facilities of the system, but most of the time they will represent aggregated groups of homogeneous transportation facilities due to data constraints.

In order to model the physical and economic characteristics of the different energy system components, parameters such as capacity, cost, and efficiency will be associated to each arc. Such parameters correspond to the equivalent parameters of the aggregated facilities. Associated with each arc (i, j) are the following parameters:

- **Lower bound**, $e_{ij.min}$, (which can be zero) on the flow,
- **Upper bound**, $e_{ij.max}$, on the flow (also called capacity),
- **Cost**, c_{ij}, per unit of flow,
- **Efficiency** parameter, η_{ij}, (sometimes called the gain or the loss factor) which multiplies the flow at the beginning of the arc to obtain the flow at the end of the arc. These multipliers are used to represent, for instance, natural gas extraction losses, electric transmission losses along power lines, or any other type of efficiency measurement. They can also be used to transform flows along arcs from one unit of measurement to another,

like for example transformation of short tons of coal to million Btu (MMBtu) or thousand cubic feet (Mcf) of gas to MMBtu.

2.1.3 Flows

A flow in an arc represents energy moving between the facilities connected by that arc. The energy flows units are Mcf (thousand cubic feet) in the natural gas subsystem, short-tons in the coal subsystem, and MWh in the electric subsystem. In the arcs corresponding to the generators, the flows are converted from their standard units into MWh using appropriate conversion factors for coal short-tons and natural gas cubic-feet in the efficiency parameter mentioned earlier. Note that in the network model, flows in the different arcs correspond to the decision variables in a minimum cost flow or a maximum flow problem, as it will be explained in Chapter 4.

2.1.4 Analysis time frame

We confine our analysis to a medium term operational time frame, e.g. one season or one year. Although the model is suitable to be applied to shorter or longer time frames, there are some benefits associated with choosing one year, because of the cyclic pattern followed by the energy flows that are mainly driven by weather conditions. For instance, during the winter the demand of gas for heating purposes increases, which decreases the availability and increases the prices of this energy source delivered to the power plants. On the other hand, the electric energy demand is higher during the summer (due to air conditioning), which leads to a larger requirement of raw energy from the power plants and the consumption of the energy from the storage facilities. Hydroelectric energy availability (due to rainfall and snow runoff) also follows a cyclic behavior due to seasonal changes in weather conditions.

2.1.5 System-specific time steps and storage

Each subsystem is modeled using a different number of time steps selected according to the particular characteristics of the respective subsystems. For instance, since the coal subsystem has relatively slower dynamics than the electric and the natural gas subsystems, it can be modeled using a smaller number of time steps than the time steps in the other subsystems. The multi-period decomposition is illustrated in Figure 2.1, where an electric demand node (LD) is decomposed in 3 time periods for each period in the fossil fuel side. The arc connecting GS1 and GS2 correspond to the energy carried over from one period to the next in storage. The multi-period network flow model can be interpreted as a replication of the respective part of the network at each point in time, with the arcs connecting the different periods hence representing temporal linkages in the system due to inventory carried over in fossil fuel storage facilities (electric energy can not be stored in large quantities). Figure 2.2 shows a high level representation of the network flow model, with different time steps for each subsystem.

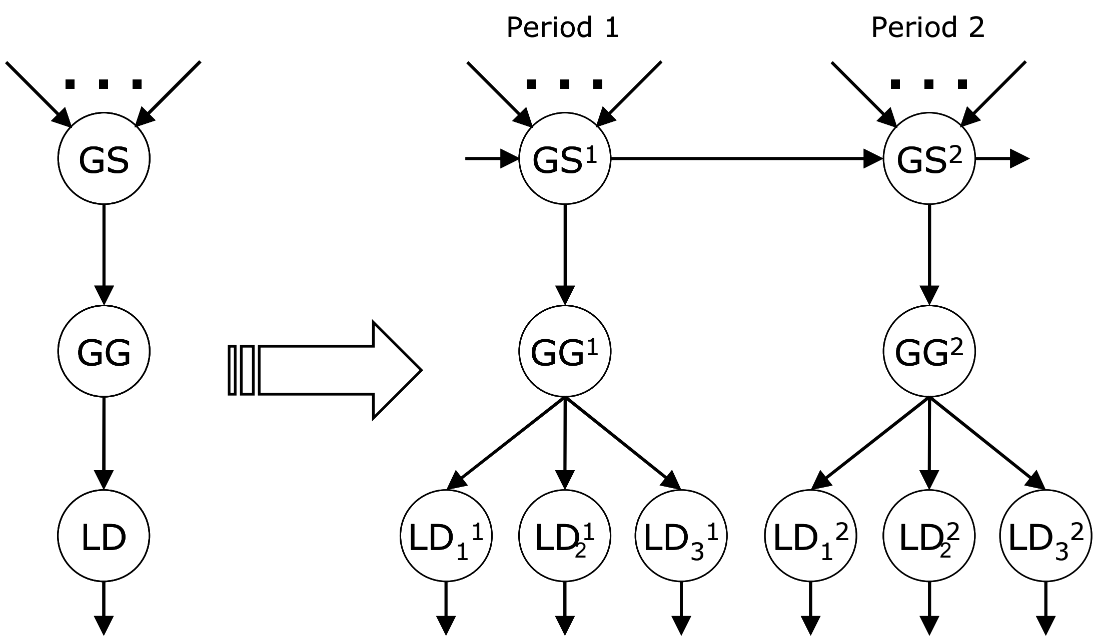


Figure 2.1. Multi-period decomposition

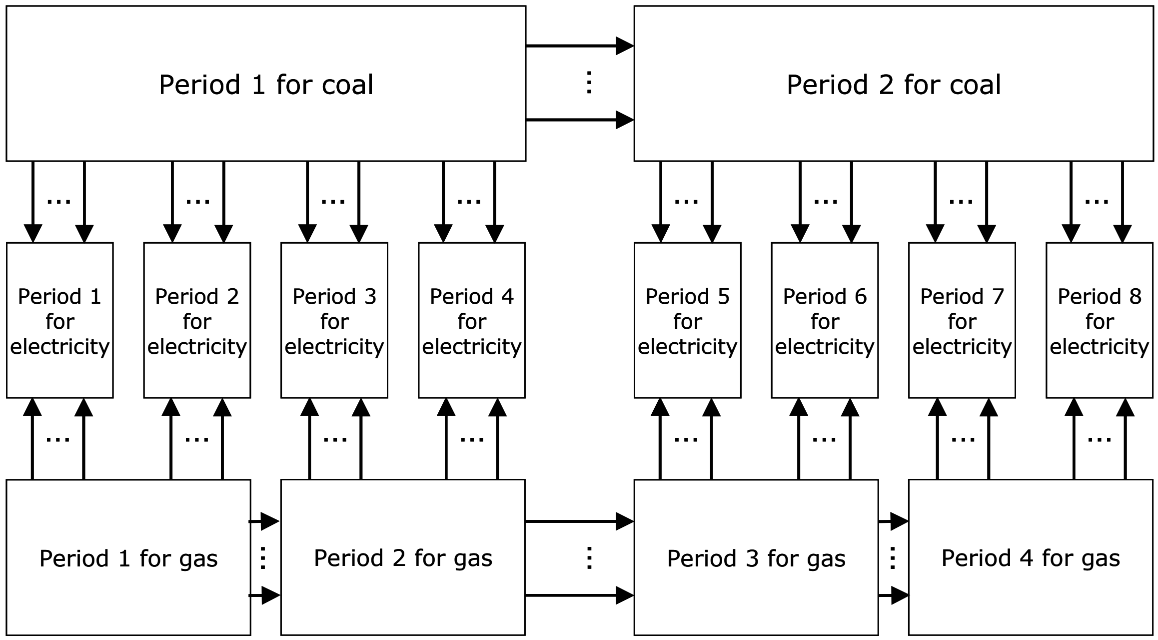


Figure 2.2. High level representation of the network flow model, with different time steps

An implicit assumption of this modeling approach is that dynamics faster than the chosen time step within a particular energy subsystem are aggregated into the time step used for that subsystem. In the final implementation of the network model using real data, and also motivated by the level of aggregation of publicly available data, the coal subsystem was modeled using a yearly time step, while the natural gas and electric subsystems were modeled using a monthly time step.

Using the previously described formulation, parameters like capacities, costs, and efficiencies in the arcs, or decision variables like energy flows will have associated a given time step. For example, an energy flow between nodes i and j at time step t could be annotated as $e_{ij}(t)$. However, to simplify notation in further developments, most of the time the index indicating the time step will not be explicit but implicit.

2.1.6 Linearization of costs and efficiencies

The input-output characteristic of a steam turbine generator can be represented by a convex curve [Wood & Wollenberg, 1996]. When multiplied by the fuel cost, we obtain the generating unit cost as a convex function of the flow. Total cost functions can then be approximated by piecewise linear functions, which leads to step incremental cost functions. In a network flow representation, each linearization segment is modeled by an arc, with the number of arcs determining the accuracy of the approximation. Figure 2.3 illustrates this concept. The cost associated to the flow in this arc is a convex function and can be fit by a piecewise linear cost function. This cost function tells us that the first 20 units of flow have a unit cost of \$2.5, the next 10 units of flow have a unit cost of \$5, and any additional amount has a unit cost of \$10, up to the capacity of 40 units of flow. As shown in Figure 2.3, this situation is modeled using a set of arcs, one for each segment of the piecewise linear cost function. Because the unit costs are increasing, the flow in a given arc will only be positive if all the other arcs with smaller unit costs have reached their capacity limits, which guarantees that the solution makes physical sense.

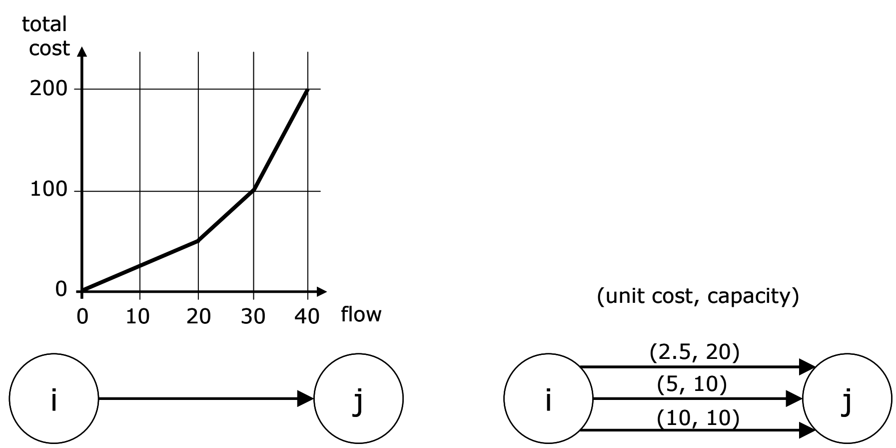


Figure 2.3. Representation of convex cost functions

Efficiency parameters may also be modeled using piecewise linear functions and can be represented by the multiple arc transformation illustrated in Figure 2.3. For example, power losses along the transmission lines are proportional to the square of the flow, and efficiency can therefore be approximated by a piecewise linear function where the slopes decrease with the flow. In this situation, it is guaranteed that the arcs with the higher efficiency parameters (lower losses) will be filled up first, since they require the smallest amount of flow, and thus the smallest cost, for the same energy demanded at the head node.

Using the previously described formulation, parameters like costs and efficiencies in the arcs, or decision variables like energy flows will have associated a given linearization segment. For example, an energy flow between nodes i and j using the linearization segment l should be annotated as $e_{ij}(l)$. However, to simplify notation, most of the time the index indicating the linearization segment will not be explicit but implicit.

2.1.7 Nominal capacity relaxation

In the actual operation of energy systems, it is not uncommon to see some facilities operating beyond their nominal operating capacities (for system reliability or market conditions) for reasonably short periods of time. In fact, from the data collected for 2005 it could be observed that for some of the months the actual energy generated by some coal-fired power plants exceeded by a small percentage their nominal capacity. This might have been motivated due to the limits imposed to the gas production and transmission capacities by hurricanes Katrina and Rita, or because high natural gas prices may have compelled generation companies to generate as much as possible using their coal-fired units.

The capacity constraint in an arc (upper bound of the flow) can be relaxed by using a similar approach to the described in Section 2.1.7. For example, an arc could be modeled by using l arcs: the first $l-1$ arcs could be used to represent the linearization segments for normal operating conditions, and the last arc could be used to represent the additional flow over the nominal capacity that can go through the facility. By choosing an appropriate high value for the cost in this last arc (at least higher than the costs for the first $l-1$ arcs), we can ensure two things. First, the flow through the last arc will only be positive if market conditions require that the facility operates over its nominal capacity. And second, that the first $l-1$ arcs with smaller unit costs will have reached their capacity limits before there is any flow through the additional arc.

2.1.8 Electric generation

Power plants have restrictions on the flow that can pass through them (generation capacity). To model a power plant capacity, operating and maintenance cost, and efficiency, it is necessary to use a pair of nodes with an arc connecting them. The parameters of this arc determine the restrictions on the flow that pass through the respective power plant. Figure 2.4 illustrates this transformation, where the parameters (l, u, c, η) refer to the lower and upper bounds, cost, and efficiency, respectively, of the facility represented by node *i*. As mentioned before, these nodes represent aggregation of electricity generation facilities sharing a similar location, type of fuel, and technology in the model implementation.

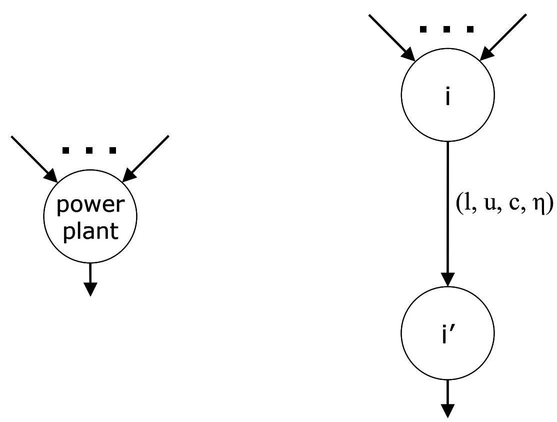


Figure 2.4. Power plant representation

2.1.9 Electric Transmission

An arc representing transmission is undirected, because the electric energy can flow in both directions. To model transmission using directed arcs, we replace the undirected arc by a couple of arcs pointing in opposite directions, as shown in Figure 2.5. If the flow in either direction has a lower bound of value 0 and the arc cost is non-negative, in the optimal solution one of the flows in the directed arcs will have a value of 0, which guarantees a non-overlapping solution.

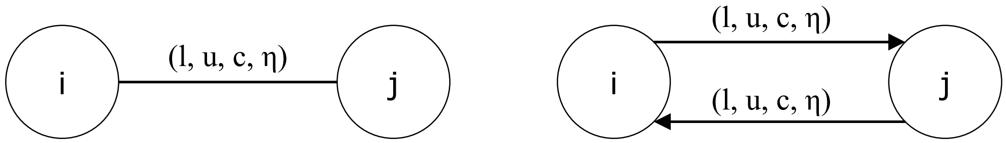


Figure 2.5. Electric transmission representation

2.1.10 Demand

In order to model energy consumption, a demand for certain nodes can be assigned. Electric load is modeled as a demand in the electric transshipment nodes. Consumption of natural gas by users other than electricity generation is modeled as a demand in the nodes representing natural gas transshipment. Coal consumption for users other than electric power is around 1% of the total, so it will be neglected.

A typical form to represent demand in power systems is a load duration curve (LDC), as the one illustrated in Figure 2.6. A LDC is a non-chronological graph that shows the amount of time (or percentage of the time) that demand is over a particular level. From the LDC illustrated in Figure 2.6 we can say, for example, that in NE-ISO during 2005 the electric load was over 10 GW during all of the time, or that approximately 5% of the time the load exceeded 10 GW. The area under the curve indicates the average load. If we calculate the product between the average load and the length of the period the LDC represents, we get the net energy for load for that period.

If the demand in one node is not constant, then the linearity of the network model is not preserved. Thus, in a first stage, demand at each period will be considered to be constant and equal to the net energy for load. The shortcoming of this approach is that by not considering distinctly the times of higher and lower load, the model provides aggregated results for the entire time step that might not reflect some effects and interactions that might happen within the period, like for example system congestion and price spikes during times of high load. Chapter 3 will discuss an improvement to the basic model in order to model different levels of load within a time step without losing the network structure of the model.

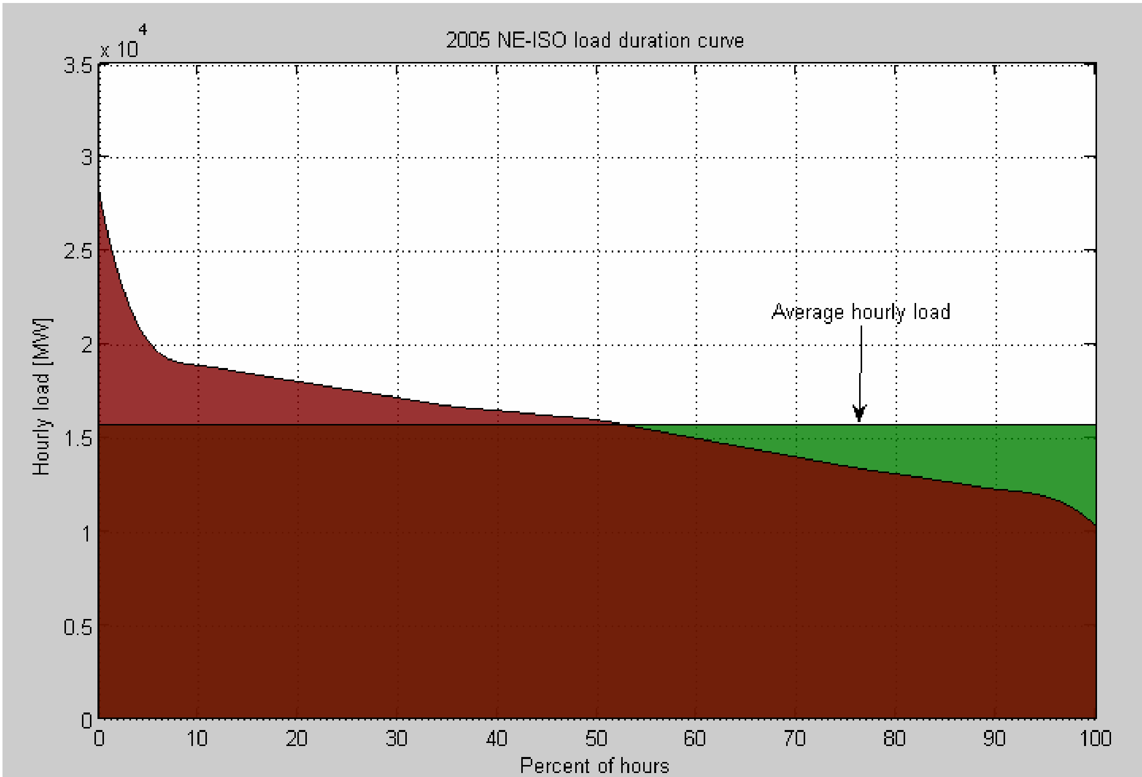


Figure 2.6. A load duration curve

Also, as a first approximation, demand at each node will be assumed to be completely inelastic, that is, independent of the energy price at the corresponding node. In other words, the demand is considered to be non-responsive to changes in price, which is a common assumption in power systems. If the demand is dependent on prices, then the linearity of the network model is lost. In later stages (as described in Chapter 3) elastic demand will be considered and incorporated through a recursive simulation.

2.1.11 Arcs with lower bounds

Lower bounds can be used to represent bilateral contracts, that is, amounts of energy that have to go though an arc due to contractual obligations. A network flow model with directed arcs with nonzero lower bounds can be replaced by an equivalent model with zero lower bounds, by using the procedure shown in Figure 2.7.

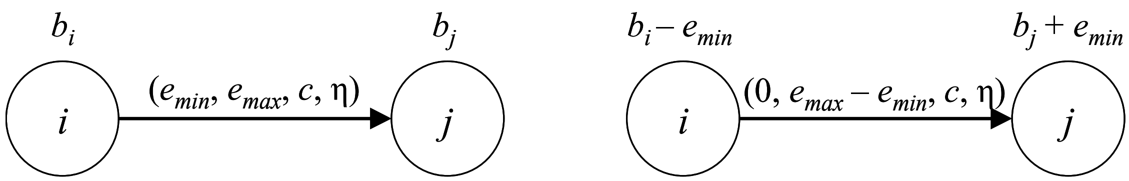


Figure 2.7. Removal of lower bounds in an arc

2.1.12 Hydroelectric generation modeling

A network model is suitable for modeling transportation of water used in the production of hydroelectric energy. For the water subsystem, nodes may represent storage facilities (reservoirs) and hydroelectric power plants. In the water subsystem, the arcs may represent rivers.

However, because of the lack of detailed data related to the movements of water for energy production, the hydroelectric system will be modeled as a direct electric energy injection into the electric transmission system. Thus, the demand in the corresponding electricity transshipment node will be reduced by an amount equal to the actual hydroelectric generation.

2.1.13 Nuclear, renewable, and other power plants

Given the lack of transportation networks associated with the production of electrical energy from other energy sources, nuclear, renewable, and other power plants are modeled in the same way than hydroelectric energy. That is, as a direct electric energy injection into the electric transmission system. Thus, the demand in the corresponding electricity transshipment node will be reduced by an amount equal to the actual electric energy produced in nuclear, renewable, and other power plants.

2.1.14 Basic matrix formulation of the problem

Mathematically, the bulk energy system operation can be simulated as a generalized minimum cost flow problem, which corresponds to an upper-bounded (or capacitated) transshipment problem that can be formulated as follows:

$$\text{Minimize } \mathbf{z} = \mathbf{c} \cdot \mathbf{e} \tag{1a}$$

subject to:

$$\mathbf{A} \cdot \mathbf{e} = \mathbf{b} \tag{1b}$$

$$\mathbf{e}_{\mathbf{min}} \leq \mathbf{e} \leq \mathbf{e}_{\mathbf{max}} \tag{1c}$$

where the energy production and transportation problem for coal and natural gas subsystems are solved simultaneously with the electricity production and transportation problem in an overall cost minimization schema. The per-unit cost vector **c** includes the costs associated with each arc. The vector of energy flows **e** includes all the decision variables. Equation (1a) corresponds to the objective function. In (1b), **A** is frequently called the node-arc incidence matrix, while **b** is the vector with the supplies/demands at each node. Each column of the incidence matrix **A** has an associated decision variable, and each row has an associated energy balance equation. There is one energy balance equation per node (with exception of production nodes). The only non-zero elements of **A** not equal to 1 nor -1 are those associated to facilities where we utilize gain factors to account for losses or efficiencies. In equation (1c), $\mathbf{e}_{\mathbf{min}}$ represents the lower bounds for the flows and $\mathbf{e}_{\mathbf{max}}$ represents the upper bounds for the flows (the arc's capacities).

For a particular node *k*, the energy balance constraint can be expressed as follows:

$$\sum_{\forall j} e_{kj} - \sum_{\forall i} \eta_{ik} \cdot e_{ik} = b_k \tag{2}$$

where e_{kj} is energy from node *k* to node *j* (outgoing flow), e_{ik} is energy flow from node *i* to node *k* (incoming flow), η_{ik} is the arc gain that is included to handle losses ($\eta_{ik} < 1$) or gains ($\eta_{ik} > 1$) that occur along the incoming arcs, b_k is the supply at node *k* if $b_k > 0$, or the negative of the demand at node *k* if $b_k < 0$.

The mathematical problem introduced above corresponds to what in operations research is called a Generalized Minimum Cost Flow Problem (GMCFP). A complete mathematical formulation and analytical framework for this problem is provided in Chapter 4.

2.1.15 Emissions

Power plant emissions are a growing concern in the energy industry. In 1963, the United States Congress passed the Clean Air Act. In the following years, it passed the Clean Air Act Amendment (1966), the Clean Air Act Extension (1970), and additional amendments in 1977 and 1990. The Clean Air Act Amendments provide the generation companies with a limited number of allowances for SO_2 emissions per year, and permit the unused allowances to be used in following years. Also, since the Clean Air Act Amendment in 1990 established a trading mechanism for emission allowances at the national level, the limit on emissions is acting as a unique system-wide constraint (given by the total number of emissions) and not as individual constraints by company or by area.

Thus, a pure network model formulation can not ensure that the total SO_2 emissions constraint imposed by the Clean Air Act Amendments is not exceeded. Therefore, another constraint must be incorporated to the mathematical formulation in order to impose a national-level limit on emissions, where the total national emissions must be equal to or less than the sum of the allowances allocated to power plants and adjusted to capture the exogenously given allowances banking effects. The amount of emissions produced depends on the fuel used, the pollution control devices installed, and the amount of electricity produced. The additional equality constraint may be represented as follows:

$$\sum_{t \in T} \sum_{(i,j) \in G} SO2_i(t) \cdot (1-\alpha_i) \cdot e_{ij}(t) \leq NSO2 \qquad (1)$$

where $e_{ij}(t)$ is the energy flowing from node i to node j during time t, $NSO2$ is the national SO_2 limit, $SO2_i(t)$ is the emissions rate associated with the fuel consumed by power plant i, at time t, α_i is the removal efficiency of the pollution control equipment installed at power plant *i* (if no pollution equipment exists at power plant *i*, then $\alpha_i = 0$), *G* is the set of arcs that represent electricity generation, *T* is the set of time periods, *i* represents the nodes associated to power plants, and *j* represents the nodes of the corresponding electric transshipment nodes.

Note that the original NEES network model plus the side emissions constraint can simulate effectively different emission compliance strategies: fuel switching (e.g., use low sulfur content coal or natural gas instead of high sulfur content coal), utilization of emissions control devices or abatement technologies (e.g., scrubbers, particulate collectors), revising the dispatch order to utilize capacity types with lower emission rates more intensively, and allowance trading. A complete description of how the NEES network model is able to handle emissions can be found in [Quelhas, 2006].

2.1.16 Uncertainty in the network parameters

Uncertainty is defined in [AIAA, 1998] as "*a potential deficiency in any phase or activity of the modeling process that is due to the lack of knowledge*". Potential modeling deficiencies in the NEES network model may be in either the network topology or in the values of the parameters in nodes and arcs. Henceforth, uncertainty will be understood as a potential difference between the estimated and the true value of a given parameter that can not be corrected by calculation or calibration. In the NEES network model, basically 3 sources of uncertainty affecting the node and arc parameters (capacity, cost, efficiency, and demand) can be identified:

- Market uncertainty: the energy movements and cost/prices depend not only on the characteristics of the network itself, but also on the perceptions and decisions of the decision makers within each company. Market uncertainty affects not only the cost parameters of the arcs, but behavioral issues in the decision making processes may deviate the actual flows from the theoretically optimal obtained by solving the GMCFP in the NEES network model.

- End-user uncertainty: demand in the nodes for a simulated scenario is not deterministic but stochastic. End-user uncertainty affects the demand in the natural gas and electricity transshipment nodes.
- Uncertainty due to disruptions, because of the possibility of failure of facilities in the energy system. This type of uncertainty affects the capacities of the arcs.

Incorporating decision makers' behavior into the NEES network model to handle market uncertainty requires extensions that are out of the scope of the current research. End-user uncertainty can be dealt with adequately in the medium and short-term horizon analysis by using acceptable predictive models and by incorporating elasticity in the demand, so the demand will be assumed to be not stochastic but deterministic. The uncertainty due to disruptions is the main concern of this research, and it will be further addressed in subsequent chapters.

2.2 Model implementation in the U.S. energy system

Due to the huge number of facilities in the NEES and the limitations on the amount and detail of data publicly available (usually at the level of state or region, without identifying the individual facilities), the facilities were aggregated taking into consideration geographical proximity and similarity on their functions and characteristics. Further refinements can be made in the model by disaggregating the nodes and arcs if more data becomes available. See [Quelhas, 2006] for another description of the model implementation assumptions and the sources of the data for a NEES network model implementation based in 2002 data.

2.2.1 Coal sub-system

2.2.1.1 Overview

According to EIA estimates, there are 267,311 million short-tons of recoverable reserves of coal in the U.S [EIA 2006b]. In 2005, 1,131 million short-tons of coal were produced in coal mines located in 32 states, with about 38% of it being produced in the

Powder River Basin in Wyoming. The coal is transported from the mines to the electric power plants (accounting for about 92% of the coal production) mainly using trains, barges, and trucks. Use of coal for electric generation accounts for about 92% of all coal production in the US.

To incorporate the particular characteristics of the coal subsystem into our integrated network model, a set of production nodes were defined, with arcs connecting them to electric generation nodes to represent the bulk movements of coal from the coal mines to electric power plants, as depicted in Figure 2.8. The nodes in the electric system representing coal-fired generation are serving as a link between the electric and the coal subsystems.

2.2.1.2 Production

To account for geological, geographical and technological homogeneities in coal production, EIA has assigned every coal mine to one of eleven coal supply regions: Northern, Central, and Southern Appalachia, Illinois Basin, Western Interior, Gulf Coast, North Dakota, Powder River Basin, Rocky Mountains, Southwest, and Northwest. Within each supply region, there is certain homogeneity in the associated production facilities. In the NEES network model, one coal production node has been assigned to each of these regions. Information about the productive capacity, average mine-mouth price, average heat value, and average sulfur content for each supply region to be used when setting the parameters of the network has been obtained from:

- EIA Form 7A ("Coal Production Report"),
- U.S. Department of Labor, Mine Safety and Health Administration, Form 7000-2 ("Quarterly Mine Employment and Coal Production Report"), and
- FERC Form 423 ("Cost and Quality of Fuels for Electric Plants").

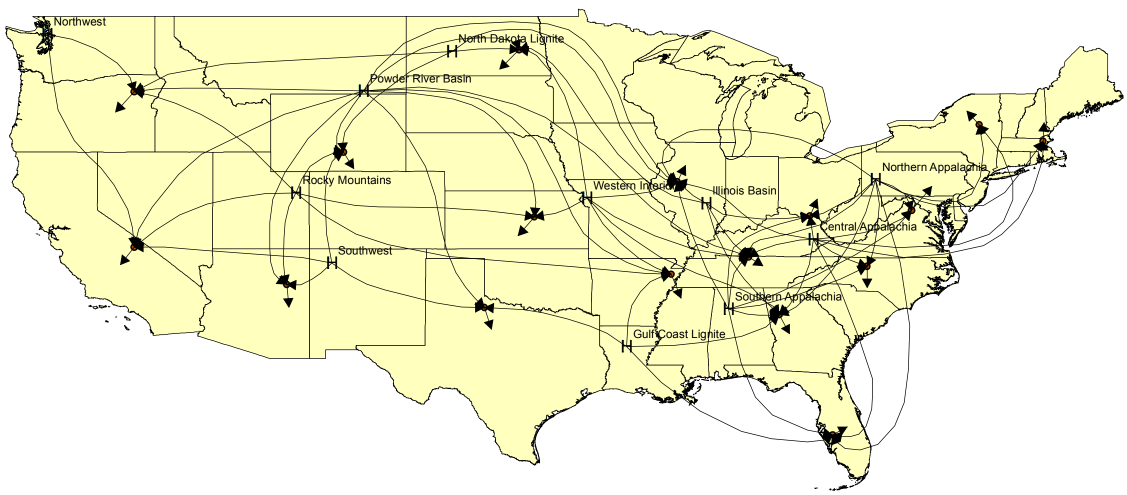


Figure 2.8. Network model of the coal production and generation.

2.2.1.3 Transportation

The coal is transported from the mines to the electric power plants using mainly trains, barges, and trucks. Given the complexity of the coal transportation system and the lack of publicly available data, it is not feasible to model individually the different transportation routes and modes. Consequently, the coal transportation system is modeled by setting up an arc between the coal production nodes and the feasible coal-fired power plants. The feasibility of the arcs is determined by economical or physical considerations. To take contracts between coal suppliers and power plants into consideration, lower bounds were considered in the capacity of the arcs. Parameters for the arcs were obtained from:

- FERC Form 423 ("Cost and Quality of Fuels for Electric Plants") and
- EIA's Coal Transportation Rate Database.

2.2.1.4 Consumption

About 92% of the coal produced in the U.S. in 2005 was consumed in electric power plants. The electric power sector uses a type of coal called steam coal, while much of the coal used by the industrial sector is metallurgical coal or coking coal, which is a selected bituminous coal produced primarily in the Appalachian Basin and characterized by high heat value and low ash content. From the remaining 8% of the coal produced in the U.S. in 2005, less than 0.4% was used by the commercial and residential sectors, around 2% was coking coal destined to coke plants, and the rest was used by the industrial sector, approximately half of it being metallurgical coal and the rest being steam coal.

To model coal consumption we first notice that the steam coal used by the industrial, commercial, and residential sectors is relatively small, and that the capacity of the coal transportations arcs is not constrained. Thus, the total demand of steam coal by non-electric consumers can be modeled as a fixed demand on a dummy node directly connected to the coal production nodes using arcs with infinite capacity and zero cost without loosing much precision. The demand of the electric consumers (generators) will be determined by the coal-fired electricity production requested by the electric power demand as a part of the optimization process and not determined exogenously.

2.2.2 Natural gas sub-system

2.2.2.1 Overview

According to EIA 2004 estimates, there are 192,513 billion cubic feet (Bcf) of consumer-grade natural gas proved reserves in the U.S. In 2005, 23,518 Bcf of consumer-grade natural gas were produced in the U.S. in more than 400,000 natural gas wells located in 32 states, with about 50% of it being produced in the Gulf of Mexico and Texas. The natural gas transportation system counts with 212,000 miles of interstate natural gas pipelines operated by 85 different companies, with a total aggregated capacity of 113 billion cubic feet (Bcf) per day.

To incorporate the particular characteristics of the natural gas subsystem into our integrated network model, a set of production, transshipment, and storage nodes were defined, with arcs connecting them to represent the bulk movements of natural gas among different facilities, as depicted in Figure 2.9. The transshipment nodes are connected to nodes in the electric system representing gas-fired generation that serve as a link between the electric and the natural gas subsystems.

2.2.2.2 Production

To account for geographical distribution of natural gas reserves and extraction facilities, we define 13 natural gas supply regions, namely: California, Other Western, Rocky Mountain, Kansas, Other Central, New Mexico, Texas, Oklahoma, Arkansas and Louisiana, Gulf of Mexico, Midwest, Northeast, Mississippi and Alabama, and Other Southeast. Data about effective productive capacity, average wellhead prices, extraction losses, and average heat value for each supply region to be used when setting the parameters of the network has been obtained from:

- EIA Form 895 ("Monthly and Annual Quantity and Value of Natural Gas Production Report") and
- EIA Form 176 ("Annual Report of Natural and Supplemented Gas Supply and Disposition"").

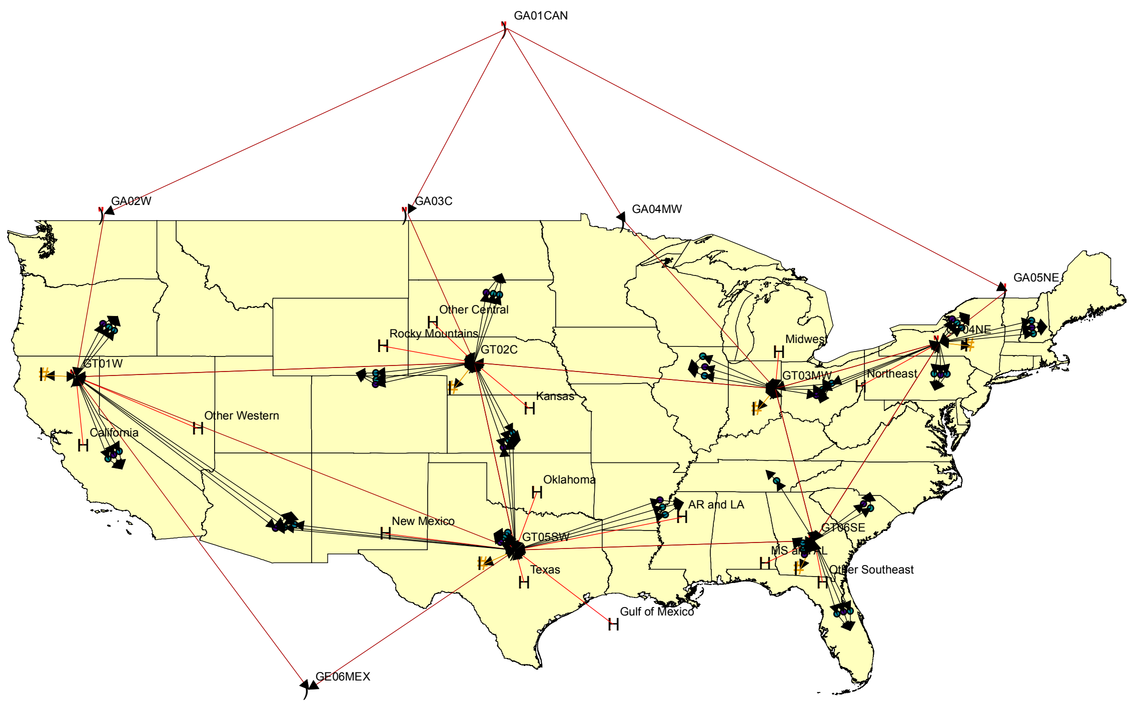


Figure 2.9. Network model of the natural gas production, storage, and generation

2.2.2.3 Transshipment nodes

Natural gas is moved from the production centers to the consumers through a very complex network of interstate pipeline flows. 6 interconnected transshipment nodes are defined based on major interstate pipeline flows, geographical considerations, and data availability restrictions. These nodes represent bulk movements of natural gas in the U.S. The nodes are called Western, Central, Midwest, Northeast, Southwest, and Southeast, and are depicted in Figure 2.8. Each node corresponds to the geographical aggregation of all the natural gas transportation facilities in each region. The arcs connecting the different natural gas transshipment nodes represent the aggregated set of pipelines that are capable of moving gas between the corresponding regions. The model also considers an additional node to represent the aggregated demand of natural gas from Mexico and additional nodes and arcs representing imports of natural gas coming from Canada.

The information about the capacities of the arcs representing the aggregated interregional pipelines and the prices and quantities of natural gas delivered to power plants have been are obtained from:

- FERC Form 549 ("Capacity Report") and
- FERC Form 423 ("Cost and Quality of Fuels for Electric Plants").

Capacity data for the natural gas imports is obtained from EIA's reports presenting aggregate data derived from the EIA's Natural Gas Pipeline Capacity Database. The monthly average prices of natural gas imported from Canada and the average heat value of this natural gas are obtained from:

- Canadian National Energy Board Form 15 ("Natural Gas Export Reporting") and
- EIA's "Annual Energy Review 2005".

2.2.2.4 Storage

Natural gas can be stored in depleted natural gas and oil fields, aquifers, and salt caverns. 6 storage nodes are defined in the model, one node for each one of the transshipment nodes. These storage nodes represent the aggregation natural gas storage facilities within each region. To account for the amount of gas that exists at the beginning and at the end of the simulation period, we set a fixed exogenously determined supply and demand in the nodes corresponding to the storage facilities in the region in the first and in the final time step respectively. The initial and final volumes in the storage nodes are determined exogenously by long-term decision models. The initial and final volumes in the storage nodes, the storage capacity, and the withdrawal and injection capacity were derived and estimated from the EIA Form 191 ("Monthly Underground Natural Gas Storage Report").

2.2.2.5 Consumption

Since only approximately 25% of the total natural gas consumption is used to generate electricity, a framework that properly models transportation of natural gas needs to take into account the demand for non electrical generation uses. The model of natural gas consumption for non-electric power sectors is done by setting an exogenously given demand in the natural gas transshipment nodes. Monthly consumption data by end-use sector can be obtained from:

- EIA Form 857 ("Monthly report of Natural Gas Purchases and Deliveries to Consumers") and
- EIA's "Natural Gas Monthly" reports.

To account for contracts between natural gas suppliers and electric power plants, lower bounds were set up in the arcs connecting the corresponding transshipment nodes and the generation nodes. The data for these lower bounds was obtained from:

- FERC Form 423 ("Cost and Quality of Fuels for Electric Plants").

2.2.3 Electricity sub-system

2.2.3.1 Overview

According to EIA data, in the 2005 year 1,046 million short-tons of coal, 211 million barrels of oil, and 6,486 Bcf of natural gas were burned for electricity generation and combined heat and power, of which 4,054,688 GWh of electricity energy were produced. Out of it, due to transmission and distribution losses and power plant use, only 3.815 millions GWh of electric energy were delivered to consumers.

The electric system can be aggregated in many different ways, depending on the characteristic of the study. The North-American Electric Reliability Council (NERC) considers aggregation at the regional level, based on the topology of the electrical transmission system and operating constraints. This level of aggregation constitutes an adequate simplification of the complexities of the electric power industry, and it will be used in our model. To incorporate the particular characteristics of the electric subsystem, a set of transshipment and generation nodes were defined for each NERC sub-region.

2.2.3.2 Transshipment nodes

A unique electricity transshipment node is defined for every one of the 17 NERC sub-regions:

- Western Electricity Coordinating Council (WECC) 4 sub-regions: Northwest Power Pool Area (NWPP), California Power Area (CPA), Arizona-New Mexico-Southern Nevada Power Area (AZNM), and Rocky Mountain Power Area (RMPA),
- Mid-Continent Area Power Pool (MAPP), now called Midwest Reliability Organization (MRO),
- Southwest Power Pool (SPP),
- Electric Reliability Council of Texas (ERCOT),
- Reliability First (RF) 3 sub-regions: Mid-America Interconnected Network (MAIN), East Central Area Reliability (ECAR), and Mid-Atlantic Area Council (MAAC),
- Southeastern Electric Reliability Council (SERC) 4 sub-regions: Entergy (EES), Tennessee Valley Authority (TVA), Virginia-Carolinas Area (VACAR), and Southern Company (SOCO),
- Florida Reliability Coordinating Council (FRCC)
- Northeast Power Coordinating Council (NPCC) 2 sub-regions: New York ISO (NYISO) and ISO New England (ISONE).

The network model of the electric system is depicted in Figure 2.9.

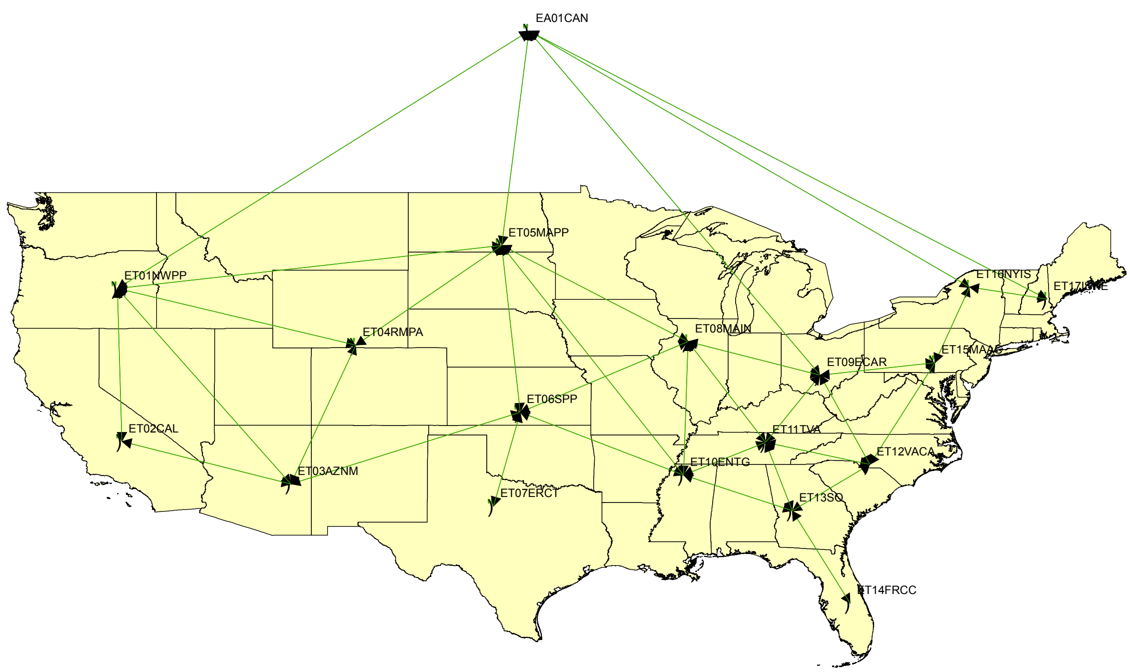


Figure 2.10. Network model of the electricity transmission.

2.2.3.3 Generation

One generation node of each type will be assigned to each of the transshipment nodes corresponding to every NERC sub-region. There are several generation nodes categories, one for each type of fuel and technology used: coal steam for coal-fired power plants, and gas steam, combined cycle, and combustion turbine for gas-fired power plants. Coal-fired units are also disaggregated by type of installed SO_2 pollution control device (no scrubber, wet scrubber, dry scrubber, and reagent injection) to take into account environmental constraints. Each generation node is connected to the transshipment node corresponding to its region by an arc in which capacity, cost, and efficiency parameters concentrate the characteristics of the power plants. The parameters for the generation nodes in each sub-region are obtained from:

- FERC Form 549B (“Capacity Report”),
- FERC Form 423 (“Cost and Quality of Fuels for Electric Plants”),
- NERC ES&D database, and
- EIA Form 906.

Also, the generation nodes are connected to the nodes in the natural gas and coal subsystems that provide them with primary energy, as explained in previous sections.

2.2.3.4 Transmission

Bulk movements of electric energy in the transmission system among different NERC sub-regions can be represented as flows in the arcs connecting the different electricity transshipment nodes. To measure the capacity of the aggregated transmission represented by these arcs, a measure called Total Transfer Capability (TTC) has been used. The TTC corresponds to the aggregated capability of a transmission system to reliable transfer electric power in an interconnected network. TTC values are obtained from:

- NERC Winter and Summer Reliability Assessments,
- WECC “Adequacy of Supply Assessment Report”, and
- NPCC’s TTC-ATC website.

Contracts to transfer electric energy between sub-regions are modeled as lower bounds, in a similar manner than in the natural gas subsystem. The values of these bounds are obtained from the NERC reliability reports. Transmission costs are derived from EIA’s “Electric Power Annual 2005”, and correspond to an estimation of the wheeling costs, i.e., the cost incurred by specific electricity transactions using the network. Transmission efficiency is set to 0.98, value obtained from EIA Form 861, found in the “Annual Electric Power Industry Report”.

2.2.3.5 Consumption

Electricity consumption is modeled by setting an exogenously given demand in the electricity transshipment nodes. Monthly consumption data by end-use sector has been obtained from:

- NERC ES&D database, originally derived from EIA Form 411 ("Coordinated Bulk Power Supply Program Report", and
- FERC Form 714 ("Annual Electric Control and Planning Area Report").

2.3 NEES network model implementation

2.3.1 2002 NEES network model implementation

The model presented in sections 2.1 and 2.2 has been already implemented and subjected to a limited testing using 2002 data [Quelhas, 2006], [Quelhas et al., 2007]. The model validation for the 2002 NEES network model implementation reported aggregated results of the simulations, with annual total flows and annual average prices. Even though overall those results constituted a good match for the actual system operation, no figures were presented to compare actual data with simulated results in time.

Actual monthly data indicates that 2002 was a relatively normal year, with no sharp short-term increases in prices nor major perturbations or large-scale contingencies worthy of specific analysis. In summary, 2002 was a 'normal' year, and the validation approach presented in [Quelhas, 2006] and [Quelhas et al., 2007] seems to be appropriate in that context.

2.3.2 2005 NEES network model implementation

Data gathering for the implementation of the basic network model (without the improvements described in Chapter 3) using 2005 data followed a very similar process to the one followed for the NEES network model implementation using 2002 data presented in [Quelhas, 2006]. Some noteworthy differences are:

- Inclusion of a new set of nodes and arcs to represent the existence of another SO_2 pollution control device for coal-fired generating units (reagent injector),
- Actualization in the definitions of some NERC regions and sub-regions,
- Changes in the way some parameters are estimated due to some new restrictions imposed to the data that can be made publicly available by EIA,
- Corrections of some minor miscalculations,
- Minor corrections in the way of modeling the final time-step of natural gas storage facilities,
- Update of all the network parameters to 2005 available data.

Due to a series of shortcomings to be discussed in Chapter 3, the NEES network model as described so far is not able to properly simulate drastic changes in the network parameters as the ones caused by major disruptions in the NEES facilities. Chapter 3 will explain some necessary improvements made to the NEES network model so that major disruptions in the NEES operation can be appropriately simulated.

2.3.3 Hurricanes Katrina and Rita

Unlike 2002, hurricanes Katrina and Rita, despite their dramatic cost in terms of human lives, made of 2005 a very interesting year for testing the performance in time of the model and to identify underlying system interdependencies. Interdependence in this context is understood as the relationship between two facilities through which the state of one of them is influenced or is correlated to the state of the other.

System interdependencies are hard to notice under normal operating conditions, but when a major perturbation strikes the system, these interdependencies are likely to be revealed. The collection of data of such events and its posterior analysis is of high utility to adequately model the interdependencies and dynamics of the energy system and so to recognize the essential infrastructure that, if disrupted, may adversely affect the performance of other infrastructure.

Besides the basic compilation of network parameters (for the arcs, lower and upper bounds, efficiencies, and costs, for the nodes, demands and storage levels at the beginning and end of the time horizon), for the 2005 model it became necessary to collect specific data on how hurricanes Katrina and Rita affected these network parameters and to characterize the effects of the 2005 hurricanes on the U.S. bulk energy transportation system. This task was performed in the context of a NSF-ECS funded research project entitled "*Data collection following Katrina: Interdependencies across time, space, and subsystems characterizing bulk energy transportation*" [McCalley & Gil, 2006].

Data was gathered for the electric, natural gas, and coal bulk production and transportation sub-systems, since these are the core energy systems incorporated into the NEES model. The collected data reflects the hurricane's effects in terms of changes in production, transportation, storage, and prices of different energy forms. Where possible, data was gathered to reflect conditions given months or years before and for the months following the hurricanes. Data sources include daily situation reports issued by the Department of Energy's Office of Electricity Delivery and Energy Reliability (OE), Energy Information Administration (EIA), Louisiana Public Services Commission, North America Electric Reliability Council (NERC), Mineral Management Service (MMS), Office of Pipeline Safety (OPS), Pipeline and Hazardous Materials Safety Administration (PHMSA), and on-site interviews, news releases, and financial releases offered by energy companies affected by the hurricanes, among others.

The main motivation behind this data collection effort was to obtain data for use in validating the simulation tools associated to our NEES model, and also to better understand the nation's bulk energy transportation systems behavior during extreme events. In particular, of special interest in the light of this research's objectives was to collect data on:

- Changes in capacity and cost of the arcs as a result of disruption in facilities affected by the hurricanes.

- Actual monthly flows and energy prices for comparison of actual and simulated results for validation purposes.

Chapter 5 will present some of the data collected for this project and the main conclusions of the post-Katrina collection effort in the context of NEES reliability.

3 Improvements to the basic model for the study of disruptions

The basic modeling assumptions as described in Section 2.2 for the NEES network model are appropriate for the system operating under normal conditions. However, under the effects of a major contingency, it may be the case that some of those assumptions may be too restrictive so that they may limit the validity of the results. Therefore, some additional features need to be added to the basic model in order to analyze the effect of disruptions in the energy movements and prices.

Section 3.1, *Avoiding infeasibilities*, discusses the necessary modifications to the network model in order to avoid infeasibilities as a result of not having enough system capacity to satisfy the demand after a large disruption. Section 3.2, *Storage decoupling*, describes the issue of storage decoupling made necessary in order to avoid disruption effects on pre-disruption decision variables. Sections 3.3 and 3.4 describe some improvements made to the model of the demand in the context of the NEES network model presented in Section 2.1, especially for what is related to simulation of large disruptive events.

3.1 Avoiding infeasibilities

The use of a network linear programming solution approach in order to obtain a minimum-cost pattern of energy movements makes the implicit assumption that the model is able to satisfy the demand. However, due to the effects of a major contingency, it may be the case that the generalized maximum flow algorithm used by CPLEX is not able to find a feasible solution to the optimization problem, that is, that the network is unable to supply the energy demand. In other words, it may be the case that there is not feasible flow able to either locally or globally satisfy the demand of electricity, coal, or natural gas (for uses other than electricity generation).

To overcome the possibility of infeasible solutions, some adjustments to the network model are necessary. The solution implemented is to add 2 so-called dummy supply nodes to the network model. The first dummy node is directly connected to all the electric transshipment nodes and the second one to all the natural gas transshipment nodes. The capacity of the arcs connecting the dummy nodes to the transshipment nodes will be unconstrained, so that any possible demand in the transshipment nodes can be satisfied. The costs associated to these arcs are required to be higher that the cost of other possible paths to supply the demand at the corresponding transshipment node. To make the model more realistic, this cost should have correspondence with the failure cost, that is, the cost of the demand not-served. Since the failure cost is very high compared to the costs under normal operating conditions (or under operating conditions in which the network is able to satisfy the demand), there only will be flow in those arcs when the existing available network capacity is not enough to satisfy the demand, and such flow will correspond to the demand not served.

3.2 Storage decoupling

One of the decision variables modeled as a flow in the NEES network model is the amount of fossil fuels carried over from one period to the next in the storage facilities. Because of the capability of storing fossil fuels for their use in subsequent periods, decisions in the NEES are coupled in time, that is, system operation and performance in future time steps depends on the amount of fossil fuel going to storage during the present period.

Moreover, energy prices in time are flattened by the effect of the storage. On the one hand, the use of fuel in storage facilities can displace the use of the most expensive thermal generation during periods of high demand, decreasing energy prices. On the other hand, fossil fuels production during periods of low demand increases so that it can go to storage facilities, increasing energy prices. Storage is also important to dampen the negative effect that system disruptions might have in prices.

The purpose of the NEES network model is not to replicate a historical occurrence but to identify the optimal way to operate the system. However, for some specific uses like for example validation of the assumptions and parameters of the model or to build a reference case, it becomes necessary to do some changes to the network in order to reproduce reality more truthfully. Since the decision variables (flows) for every time step are determined simultaneously, that is, the optimization process treats the entire multi-time-period network as a single static network and finds the optimal way to satisfy the demands on that network, when trying to replicate the effects of a disruption this approach would imply previous knowledge by the centralized decision maker that the system disruption is going to happen. For example, if decision makers had known in January 2005 that hurricanes Katrina and Rita in Fall 2005 were going to have a big impact in natural gas production and transportation, they would have started storing as much natural gas as possible during the first months of the year so that they could release it once the production and transportation of gas has tightened and the prices increased as a result of the disruption. The result of this are flattened nodal price curves that do not reflect reality. Such effect could be clearly observed in some preliminary simulations for the 2005 NEES network model.

An interesting possibility to deal with this situation when trying to replicate the actual system operation is to make decisions for each month considering uncertainty of what is going to happen next, by assigning probability distributions to network parameters in a stochastic programming framework. Stochastic programming is like a recursive linear programming where some of the parameters have a probability distribution associated to them. Different techniques for stochastic demand and/or costs in a stochastic minimum cost flow problem framework can be found in the stochastic programming literature. Also, slack variables can be added to a capacity constraint to turn the inequalities into equations. Then, the same techniques used for stochastic demand could be used to incorporate stochastic capacities in the problem.

The stochastic minimum cost flow problem approach was not followed considering that: 1) it would be considerably more cumbersome to implement than the approach finally used, 2) it assumes previous knowledge of probability distributions associated to the arc capacities, which are not known in practice, and 3) the NEES network model corresponds to a generalized network, which would complicate things even further.

An alternative approach that is considerably simpler to implement is to decouple the network such that the pre and post contingency decisions are independent. This independence can be achieved by eliminating the arc corresponding to the storage carried out from the period immediately before the contingency and the period immediately after the contingency. This arc elimination would also imply the need to assign a demand to the storage node corresponding to the time step immediately before the contingency equal to the actual storage level at the end of the period, and to assign a supply to the storage node corresponding to the time step immediately after the contingency equal to the actual storage level at the beginning of the period. In summary, the pre and post-event storage decisions are being decoupled by severing the link that the storage constitutes.

The effects of hurricanes Katrina and Rita in the NEES network model were simulated with and without applying the decoupling procedure. It could be clearly observed in the results that, without applying the decoupling procedure, nodal price curves were more flat than expected, since more natural gas went to storage in the months previous to the hurricanes (raising the prices for those months) and more natural gas was released from storage in the months after the hurricanes (lowering the prices). With the use of the decoupling procedure the nodal prices followed a similar pattern than the followed by actual energy prices, as presented in Section 7.1.

3.3 Demand elasticity

Certainly, the energy demand is highly inelastic (that is, not very dependent of changes in prices), so the assumption of inelastic demand under normal operating conditions is appropriate. However, under the effects of a major contingency, congestion may lead to large price peaks either locally or globally, and therefore the reduction in the demand may be noticeable and worthy of consideration. Thus, under the effect of a major disturbance, the prices may increase so much that the assumption of demand inelasticity originally established for the model may not hold true.

Demand may change as a result of several determinants: weather, price of the commodity, and prices of other commodities, among others. For example, colder weather in the winter or warmer weather in the summer may lead to demand increases, which in turn augment the energy flows in the network, the system congestion, and the nodal prices. Or high prices of natural gas might, for example, lead to a reduction in the use of natural gas for heating, or to substitute it by electricity.

Demand elasticity is the percent change in the demand during a period of time divided by the percent change in a particular demand determinant. But since some of the demand determinants are not independent from each other, the individual effects of one determinant may be difficult to establish. For example, the effect of contingency in the production and/or transportation of natural gas (such as what happened with hurricanes Katrina and Rita in 2005) may lead to an increase of its price. Now, if residential users would switch from natural gas to electricity for heating, more fossil fuels may be required by the power plants to satisfy the increase in the electric demand, driving up the electricity prices as well. In the end, it is difficult to establish values for elasticity in the demand of a particular energy form as an effect of one individual demand determinant, and most of the time empirical approaches to obtain elasticity values will suffer of some level of feedback across determinants. Another factor to consider is that short-term demand elasticity is different from long-term demand elasticity, because of technology substitution possibilities in the long-term.

EIA [Costello 2006] provides some elasticity values for natural gas demand obtained by using multiple simulations over a 2-year horizon from their Regional Short-Term Energy Model (RSTEM). Table 3.1 shows the values for natural gas demand elasticity with respect to natural gas prices for different types of users as calculated in [Costello, 2006]. Then, if natural gas prices increase by 20%, the demand of natural gas in the industrial sector will decrease by approximately 5.4%.

Table 3.1. Natural gas demand elasticity by type of consumer

Residential	-0.042
Commercial	-0.055
Industrial	-0.269
Electric power	-0.138
Total	-0.137

Note that in the NEES network model the consumption of natural gas for electric generation is not an exogenously given demand but a decision variable. Therefore, the electric power sector does not require an elastic demand. Besides, the natural gas transshipment nodes aggregate all the demand for non-electric consumers, that is, residential, commercial, and industrial consumers. Hence, a single value for natural gas elasticity of demand for non-electric consumers can be calculated using a weighted average where the weights are given by the total consumption of natural gas by each sector. Thus, the value for the elasticity to be used for natural gas elasticity in the 2005 NEES network model is -0.148.

Since there are no readily available substitutes in the short-term, an electric demand reduction would make consumers suffer unacceptable disruptions in operations. Thus, in the short run, demand elasticity for electricity is near zero, that is, there is little or no reduction in demand as prices rise. In the long term, however, users can shift to different technologies, by implementing load management techniques or by switching to alternative energy sources. A reasonable value for elasticity of electric demand for the residential and commercial sector is -0.1. Such value has been used in some mid-term studies performed by EIA and will be also used here.

A practical and very important concern is that with elastic demand the network problem will no longer be linear since the value of an elastic demand would depend on the dual solution of the GMCFP. Therefore, it would not be possible to take advantage of the readily available network simplex algorithms and the simulations would require a far more sophisticated technique. The incorporation of elastic demand is not expected to imply a large improvement in accuracy due to the relatively small values for elasticity of demand. Thus, a compromise was reached between accuracy and solution simplicity by performing 2 iterations of the network simplex algorithm. The first iteration serves three purposes. First, it uses an initial estimate for the demands at the transshipment node, then, solves the problem and finally determines the first estimate for the nodal prices. As a result of this, a demand response mechanism takes place and the new demands are calculated, by computing the product of the percent increase in nodal prices at the natural gas and electric transshipment nodes (with respect to a base case) and the values for elasticity. Then, with the new values for the demands, a new solution is obtained by using the network simplex algorithm.

3.4 Decomposition by load levels

When discretizing a continuous process one needs to be especially careful in choosing a sample rate fast enough so that relevant information between samples is not missed. A similar idea applies when selecting the appropriate time-step size for each energy subsystem. Simulations in the NEES network model provide results that are aggregated for each time step. That is, energy flows and nodal prices within a given time step are aggregated into a single value. Thus, any dynamic or variability in the system variables occurring within a time step is lost.

Since one of the main sources of variation in electric demand occurs due to the changes in the human activity levels during any day-night cycle, a time step of a month for the electric subsystem will not reflect any of that variability, or any of the demand variability occurring within a month. Hence, a time-step size of a month might not reflect some effects and interactions that may be important to analyze when studying the effects of disruptions, like for example system congestion or price spikes that are especially noticeable during periods of high load.

Moreover, since gas fired generation is more expensive than coal-fired generation, natural gas is typically used for electricity generation when electric demand is over a certain threshold such that all coal-fired units are operating at their maximum capacity. For this reason, many natural gas power plants do not operate continuously, but only on periods of high demand. If the model is not able to represent periods when high demand occurs, then in the simulation results some of the more expensive generating units that only operate during peak demand hours will never be used, which is unrealistic and may lead to underestimate electricity prices and natural gas use for generation. The significant underestimation of natural gas use for electric generation reported in [Quelhas, 2006] is mainly an indication of this modeling shortcoming.

Electric demand variability may be described using load curves or load duration curves. A load duration curve (LDC) is similar to a load curve but the demand data is ordered in descending order of magnitude, rather than chronologically. In general, load curves are used for the operational and short-term (daily, weekly, and monthly) scheduling, while load duration curves are used for mid- and long-term (over a month) planning [Liik et al., 2004], [Billinton & Whang, 2002].

Using load curves, an hourly time step would be deemed appropriate to take most of the demand variability into account. Since electric energy can not be stored in large quantities, and minimum up and down time constraints for thermal units are not being considered, decision variables in the electric subsystem are decoupled in time. In other words, chronological order of the loads is not relevant in the context of the NEES network model. Also, most of the hourly demand data happens to be redundant, since many hours have a similar demand. The use of 8760 time steps in a year for the electric subsystem would increase the numerical complexity as many more decision variables and constraints would need to be considered, but since the simulation running times are quite small for the model as it is, the increase in the numerical complexity should not be expected to be a major problem. However, the data processing requirements for 8760 hours (in one year) in 17 transshipment nodes would make the preparation of each simulation and the post-processing of the results more cumbersome to implement. It must also be noticed that hourly data is not readily available for the level of geographical aggregation used in the electric subsystem.

An alternative approach to using load curves comes from the consideration that hours with a similar demand level can be aggregated, and the result can be represented as a load duration curve (LDC). The area under the LDC is the energy consumed over the time period. Dividing this value by the time period gives the average load. If the product between the average load and the length of the time step (1 month) is calculated, we get the net energy for load for that time period. Consequently, it can be assumed that the use of the average demand in a given time step corresponds to a single constant load level approximation of the LDC, as it was illustrated in Figure 2.6, where the average load value was approximately 1.58 MW. But if we go one step further, the demand could be more accurately approximated by a set of constant load levels as illustrated in Figure 3.1. The area under the LDC for each segment must be equal to the area under its respective load level. If the number of segments is large enough, the approximation can be very accurate.

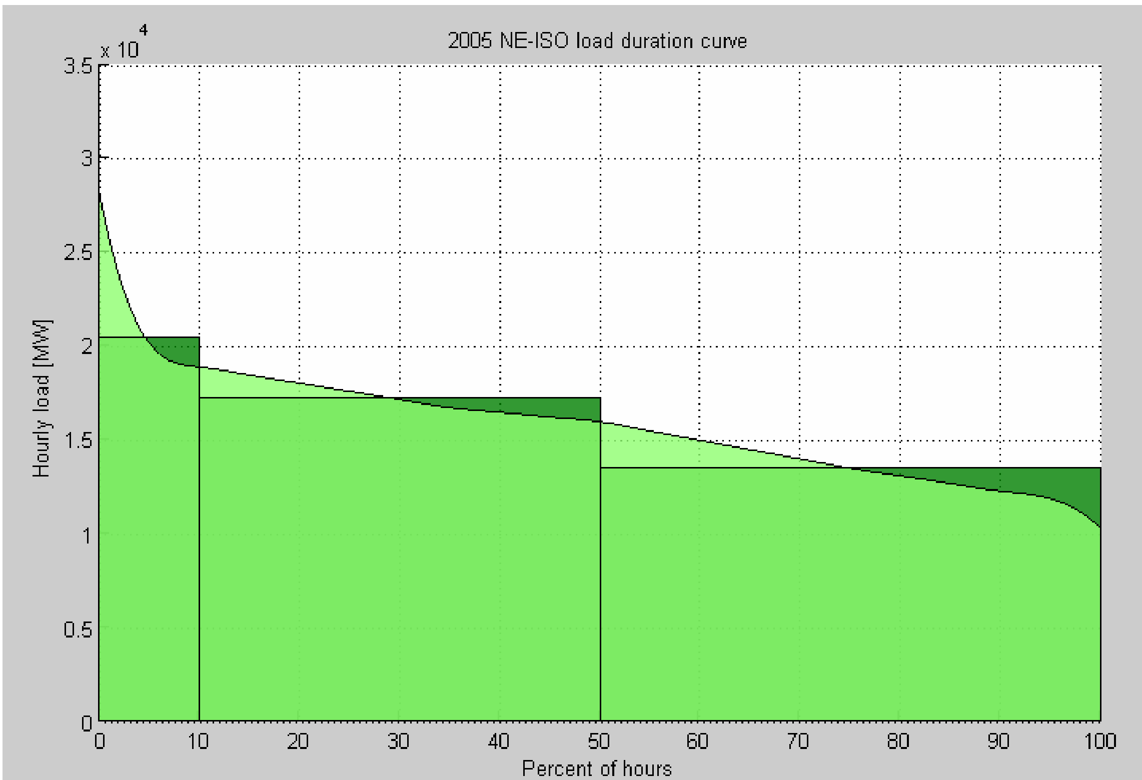


Figure 3.1. Demand representation using 3 load levels.

In the particular case of the LDC shape in Figure 3.1, 10% of the time the load was approximately equal to 1.305 times the average load, 40% of the time the load was approximately equal to 1.099 times the average load, and 50% of the time the load was approximately equal to 0.86 times the average load.

In order to preserve the network structure when incorporating the new model for the demand, it becomes necessary to expand the original network to include additional nodes able to represent the different demand levels within a time step. This was performed by decomposing the electric transshipment nodes into one node for each load level, as illustrated in Figure 3.2. The multi load-level can be interpreted as a replication of the electric transshipment nodes at each time-step. Hence, the new nodes represent a fixed load level at a given time step.

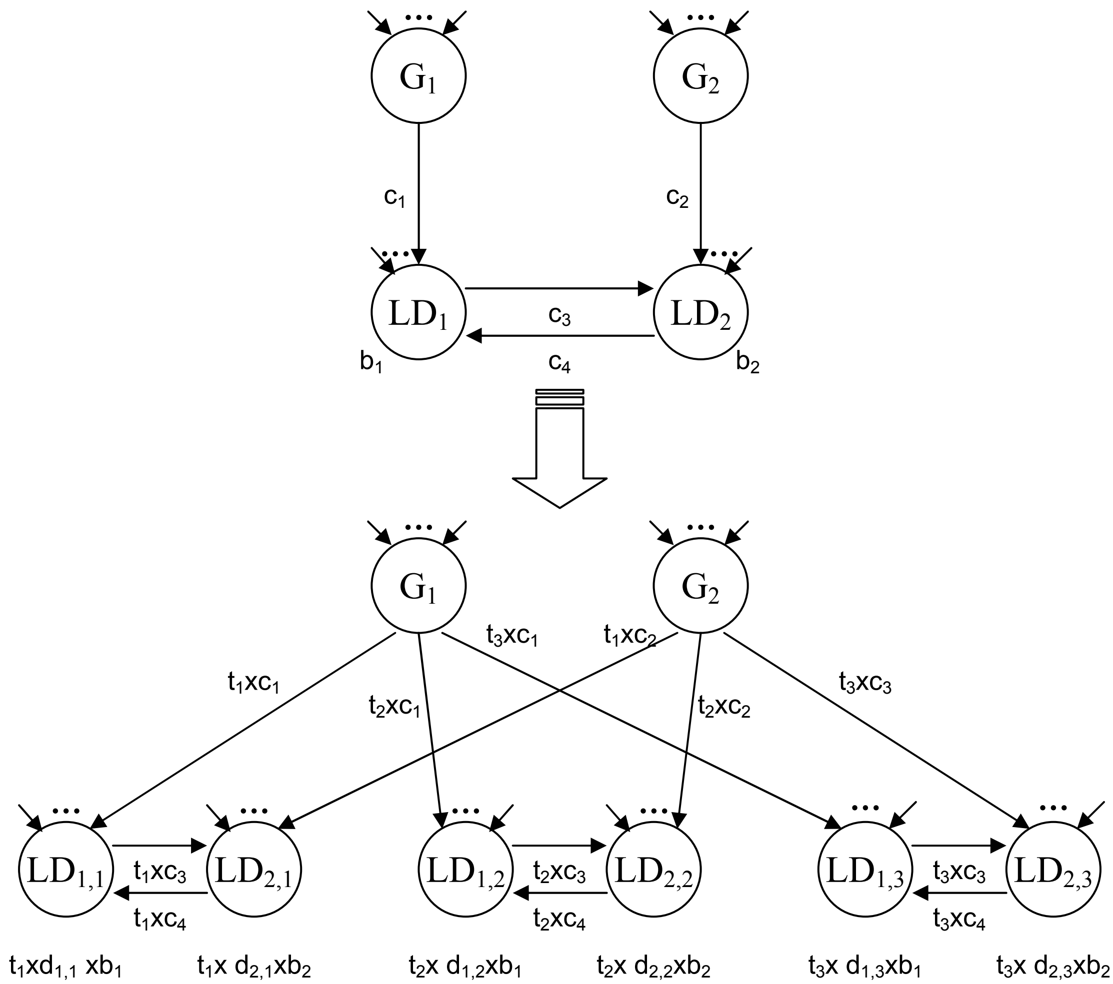


Figure 3.2. Decomposition of electric transshipment nodes by load levels.

Here, each electric transshipment node (LD_1 and LD_2) is decomposed into 3 nodes (one for each load level, indicated in the second sub-index) for each time-step. The rest of the nodes remain the same. Demand at the new nodes is now equal to the area under the respective segment of the LDC corresponding to the respective NERC sub-region. The sum of the energy demand at the 3 new nodes should be equal to the energy demand at the node they are replacing. If LD_1 corresponds to NE-ISO, then $t_1 = 0.1$, $t_2 = 0.4$, $t_3 = 0.5$, $d_{1,1} = 1.305$, $d_{1,2} =1.099$, and $d_{1,3} = 0.86$. Thus, in the case of the LDC for NE-ISO, $1.305 \cdot 0.1 + 1.099 \cdot 0.4 + 0.86 \cdot 0.5 = 1$ for the data to be consistent.

The capacities of the incoming or outgoing arcs in the electric transshipment nodes decomposed by load levels also need to be adjusted. Their original capacities before the decomposition now are multiplied by the total time they are representing (0.1, 0.4, and 0.5 in the case of the NE-ISO LDC decomposition in figure 3.2). Their costs and efficiencies are per unit of flow, so they remain the same.

An implicit assumption of the decomposition is that the periods of high, medium, and low load are coincident in each control area. If the periods of high, low, medium, and low load are not coincident for different NERC regions that are interconnected (as it may be the case of regions located in different time zones), arcs to represent energy flows between nodes symbolizing different load levels can be included, provided that their capacities are adequately selected.

Since data of load demand curves is only available for NY-ISO and NE-ISO, only these regions have been disaggregated by load levels in the simulations presented in Chapter 7. Since NY-ISO and ISO-NE are close to each other and they have similar load patterns, it is assumed that the nodes corresponding to each load level in one region are interconnected to the nodes corresponding to a similar load level in the other region.

4 Mathematical formulation and analytical framework

Chapters 2 and 3 presented how the NEES can be formulated as an integrated network with capacitated arcs. Using this model, the energy system operation can be simulated by solving 2 different problems: the Generalized Minimum Cost Flow Problem (GMCFP) and the Generalized Maximum Flow Problem (GMFP). This chapter presents the mathematical formulation of both problems and also establishes the analytical framework necessary to support the concepts and results introduced in subsequent chapters.

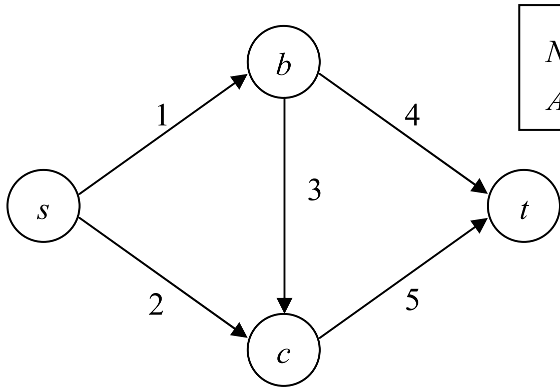
This chapter is organized as follows: Section 4.1, *Basic definitions in graph theory*, provides some background in graph theory and some definitions that will be necessary throughout the upcoming sections. Section 4.2, *Generalized minimum cost flow problem formulation*, discusses the GMCFP and some of its different formulations. Section 4.3, *Duality and optimality in the GMCFP*, discusses some results in duality theory and optimality conditions for the GMCFP, presenting the foundations for the discussion of sensitivity of the GMCFP results to changes in network parameters presented in Section 4.4. Some of the ideas presented in subsequent chapters rely heavily on the analytical framework provided by this discussion about sensitivity. Section 4.5, *Generalized maximum flow problem*, talks about the GMFP, which is relevant for the identification of vulnerabilities in the system.

4.1 Basic definitions in graph theory

Some basic definitions of terms used in graph and network flow theory are presented in this section.

4.1.1 Graphs

A graph is a mathematical structure often used to describe a network. A graph $G = (N, A)$ is defined by two sets: a set of nodes N and a set of arcs A. The arcs in the set A correspond to pairs of distinct nodes from the set N. An arc may be seen as connecting a given pair of nodes. A graph G is called directed if the arcs in the set A correspond to ordered pairs of distinct nodes of the set *N*. The first node in the ordered pair defining an arc is called the tail, while the second one is called the head. A graph *G* is called an *s-t* graph if it has two particular nodes, a source *s* and a sink *t*. Figure 3.1 shows a directed *s-t* graph.



$$N = \{s, b, c, t\}$$
$$A = \{1,2,3,4,5\} = \{(s,b),(s,c),(b,c),(b,t),(c,t)\}$$

Figure 3.1. A directed *s-t* graph

4.1.2 *s-t* paths and cuts

An *s-t* path is a set of arcs connecting the nodes *s* and *t*. An *s-t* path is called a minimal path-set if by removing any of the arcs in the minimal path-set (MP), the remaining elements are no longer an *s-t* path. In other words, a MP defines a minimal set of arcs necessary to send flow form *s* to *t*. For example, in the graph in Figure 3.1, there are 3 minimal path-sets: $MP_1 = \{1,4\}$, $MP_2 = \{2,5\}$, and $MP_3 = \{1,3,5\}$. Note that if the graph were undirected, there would be an additional minimal path-set ($MP_4 = \{2,3,4\}$).

An *s-t* cut is a partition of the node set *N* in two disjoint subsets S and $\overline{S} = N - S$, where $s \in S$ and $t \in \overline{S}$. An *s-t* cut defines a set of arcs, called cut-set, where the arcs in the cut-set have one end point in S and another endpoint in $\overline{S}$. In other words, a cut-set defines a unique combination of arc failures that can cause system failure. In a directed graph, the arcs in the cut-set have their tails in S and their heads in $\overline{S}$. A cut-set is said to be minimal, if by removing any arc in the cut-set, the remaining arcs are no longer a cut-set. For example, in the graph in Figure 3.1, there are 4 minimal cut-sets: $MC_1 = \{1,2\}$, $MC_2 = \{1,5\}$, $MC_3 = \{2,3,4\}$, and $MC_4 = \{4,5\}$.

The length $\lambda(G)$ of a graph G is the number of components in the minimal path-set having the smallest cardinality. The width $\mu(G)$ of a graph G is the number of components in the minimal cut-set having the smallest cardinality [Kaufmann et al., 1977].

4.1.3 Networks

A network $G = (N, A, \mathbf{\theta})$ is a graph with a set N of nodes and a set A of arcs and a *p*-dimensional function $\mathbf{\theta} : A \rightarrow R^p$, where *p* is the number of parameters associated to each arc. The parameters for each arc may be, for example, capacity, cost, and/or efficiency. We can make a similar formulation if we want also to include parameters in the nodes. A particular case is a capacitated network $G = (N, A, C)$, which is as a graph with a set N of nodes and a set A of arcs and a nonnegative capacity function $C : A \rightarrow R_0^+$, corresponding to the maximum capacity of the flow in the arc.

4.1.4 Flows

A feasible flow is a function $e : A \rightarrow R$ which obeys three types of constraints:

(a) Capacity constraints: for each arc, the flow must be equal to or less than the capacity $e_{ij,\max}$ associated to each arc (i, j), as expressed by

$$e_{ij} \leq e_{ij,\max}\text{, for each arc } (i, j) \in A \tag{1a}$$

(b) Conservation of flow constraints: for each node *k*, the sum of the flows from the incoming arcs is equal to the sum of the flows of the outgoing arcs plus the demand at the node, as expressed by

$$\sum_{i,(i,k)\in A} e_{ik} = \sum_{j,(k,j)\in A} e_{kj} + b_k\text{, for each node } k \in N - \{s,t\} \tag{1b}$$

(c) Non-negativity constraints: the flow in each arc must be equal or greater than 0, as expressed by

$$e_{ij} \geq 0\text{, for each arc } (i, j) \in A \tag{1c}$$

(as explained in Chapter 2, any arc with lower bound different than 0 can be transformed into a network with lower bound equal to 0).

The total flow w is a function $w : e \to R$ such that $w = \sum_{j,(j,t)\in A} e_{jt}$, which is the total flow arriving to the sink node t. The total feasible flow is also equal to the flow crossing any minimal cut-set $[S, \bar{S}]$: $w = \sum_{i\in S, j\in \bar{S}} e_{ij} - \sum_{i\in S, j\in \bar{S}} e_{ji}$.

In order to incorporate losses or gains of flow, an extra parameter to each arc (i, j) can be assigned: a gain or an efficiency $\eta_{i,j}$, and the conservation constraint is actually redefined as $\sum_{(i,k)\in A} \eta_{i,k} \cdot e_{ik} = \sum_{(k,j)\in A} e_{kj}$. A network with some of its arcs having efficiencies different than 1 is called a generalized network [Ahuja et al., 1993].

4.1.5 Residual networks

The residual capacity in an arc (i, j), with respect to a flow e_{ij}, is given by $r_{ij} = e_{ij,\max} - e_{ij} + e_{ji}$. Thus, the residual capacity indicates the maximum additional flow that can be sent from node i to j using the arcs (i, j) and (j, i). A residual network G (**e**) with respect to the vector of flows **e** consists of the arcs on the original network G with positive residual capacity.

4.2 Generalized minimum cost flow problem formulation

The GMCFP consists of finding the feasible flow with the minimum cost. As explained in previous chapters, the bulk energy system operation can be simulated as an optimization problem where the objective is to find the flow that satisfies the demand while minimizing the total operation cost. Sensitivity analysis starting from the solutions of the GMCFP can be done in order to evaluate the impact of contingencies on energy prices in different parts of the NEES.

The GMCFP assumes a centralized decision-making process, with the flows in the different arcs being the decision variables. Even though the assumption of a centralized decision maker is not completely realistic (especially after deregulation of the energy markets), the solution of the GMCFP can be used as a benchmark in order to evaluate the behavior of the system under different scenarios. The flows associated with the minimum cost flow solution (as determined by a centralized decision maker in a single objective function framework) somehow mimic the flows resulting from the interaction among energy companies and the energy market occurring in reality (multiple decision makers in a multiple objective function framework).

Each linear programming problem like the GMCFP (which for the purposes of this discussion is called primal problem) has a closely related dual problem, which is also a linear programming problem. The dual problem formulation can be useful to understand the meaning of nodal prices, in which we heavily rely in subsequent chapters to determine different system metrics.

4.2.1 Primal problem formulation

Mathematically, the GMCFP is an optimization problem that can be formulated as follows:

$$\text{Minimize } z = \sum_{(i,j)\in A} c_{ij} e_{ij} \tag{2a}$$

subject to:

$$\sum_{(k,j)\in A} e_{kj} - \sum_{(i,k)\in A} \eta_{ik} e_{ik} = b_k \qquad \forall k \in N, \tag{2b}$$

$$e_{ij} \le e_{ij.\max} \qquad \forall (i,j) \in A, \tag{2c}$$

$$e_{ij} \ge e_{ij.\min} \qquad \forall (i,j) \in A, \tag{2d}$$

where z is the objective function; A and N are the set of arc and nodes respectively; e_{ij} is the flow from node i to node j, corresponding to the decision variable on this problem; the right-hand side parameters are b_k, correspond to supply (if positive) or negative of the demand (if negative) at node k, and $e_{ij.\max}$ and $e_{ij.\min}$, which are the upper and lower bounds on the flow from node i to node j, respectively; c_{ij} is the per unit cost of the flow from node i to node j; and finally η_{ij} is the efficiency parameter associated with the arc connecting node i to node j.

The mathematical formulation above is the general formulation for any GMCFP. In the NEES network model in particular, note that $e_{ij}(t,l)$ and $c_{ij}(t,l)$ are functions of the time and the linearization segment, η_{ij} (t,l) is function of the linearization segment, and $b_k(t)$, $e_{ij.\max}(t)$, and $e_{ij.\min}(t)$ are functions of time. Therefore, equations (2a) and (2b) should also include sums over the time steps and linearization segments to take this into account. However, since the developments in the following sections are applicable to any generalized network and not only to the NEES network model, and also to make notation simpler, the functionality in terms of time step and linearization segment were omitted in the equations in order not to lose generality.

4.2.2 Dual problem formulation

The dual formulation of a linear programming problem is formulated using the fact that each constraint in the dual problem has an associated variable in the primal problem, and each constraint in the primal problem has an associated variable in the dual problem. Since there are 3 different types of constraints (plus a constraint related to emissions that is not shown in this formulation): lower bounds for each variable, upper bounds for each variable, and flow balance constraints for each node, there will be 3 types of variables in the dual problem formulation, that will be denoted with δ, μ, and λ respectively. The dual of the GMCFP is as follows:

$$\text{Maximize } y = \sum_{k\in N} \lambda_k \cdot b_k + \sum_{(i,j)\in A} \delta_{ij} \cdot e_{ij,\min} - \sum_{(i,j)\in A} \mu_{ij} \cdot e_{ij,\max} \tag{3a}$$

subject to:

$$\lambda_i - \eta_{ij} \cdot \lambda_j + \delta_{ij} - \mu_{ij} \le c_{ij} \qquad \forall (i,j) \in A, \tag{3b}$$

$$\delta_{ij} \ge 0 \qquad \forall (i,j) \in A, \tag{3c}$$

$$\mu_{ij} \ge 0 \qquad \forall (i,j) \in A \tag{3d}$$

where y is the value of the dual objective function, λ_k is the dual variable associated to the balance constraints for each node k, δ_k is the dual variable associated with the lower bounds, and μ_k is the dual variable associated to the upper bounds. Note that since λ_k is associated to a balance equation (equality constraint), λ_k is unrestricted in sign.

4.2.3 Lagrangian

The use of Lagrange multipliers is a widely used technique in constrained optimization[1]. In fact, linear programming is a particular case of constrained optimization where the objective function and the constraints are linear with respect to the independent variables. The dual formulation of a linear programming problem is closely related to the Lagrangian associated to the primal problem, which is stated in Equation (4).

$$\begin{aligned} L = & \sum_{(i,j)\in A} c_{ij} e_{ij} + \sum_{k \in N} \lambda_k \left[\sum_{\forall jk} e_{kj} - \sum_{\forall i} \eta_{ik} e_{ik} - b_k \right] + \\ & \sum_{(i,j)\in A} \delta_{ij} \left[e_{ij.\min} - e_{ij} \right] + \sum_{(i,j)\in A} \mu_{ij} \left[e_{ij} - e_{ij.\max} \right] \end{aligned} \qquad (4)$$

where λ_k is the Lagrangian multiplier associated with the balance constraint at node k. In other words, λ_k is the shadow or nodal price for node k. δ_{ij} and μ_{ij} are the Lagrangian multipliers associated with the lower and upper bound constraints, respectively, on the flow going from node i to node j.

4.3 Duality and optimality in the GMCFP

4.3.1 Duality and complementary slackness property

The strong duality theorem states that "*If one of the pair of primal and dual problems has a finite optimal solution, so does the other one and both have the same objective function values*" [Ahuja et al., 1993]. Therefore, solving the primal is equivalent to solving the dual. The primal and dual coefficients and variables are related, and that

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[1] Constrained optimization is the minimization or maximization of an objective function subject to constraints on the possible values of the independent variables.

relationship is made explicit by the complementary slackness optimality conditions theorem.

A pair of primal and dual feasible solutions is said to satisfy the complementary slackness property if it satisfies the following conditions:

$$\lambda_k \left[\sum_{\forall j} e_{kj} - \sum_{\forall i} \eta_{ik} e_{ik} - b_k \right] = 0, \qquad \forall k \in N \tag{5a}$$

$$\delta_{ij} \left[e_{ij.\min} - e_{ij} \right] = 0, \qquad \forall (i,j) \in A \tag{5b}$$

$$\mu_{ij} \left[e_{ij} - e_{ij.\max} \right] = 0 \qquad \forall (i,j) \in A \tag{5c}$$

$$e_{ij} \left[c_{ij} - \lambda_i + \eta_{ij} \cdot \lambda_j - \delta_{ij} + \mu_{ij} \right] = 0 \qquad \forall (i,j) \in A \tag{5d}$$

4.3.2 Optimality conditions

The complementary slackness optimality conditions theorem states that "*A primal feasible solution and a dual feasible solution are optimal solutions of the primal and dual problems if and only if they satisfy the complementary slackness property*" [Ahuja et al., 1993]. A straightforward consequence of the theorem is that the product of the slack in the constraint and its associated primal or dual variable is 0. Therefore, the dual variables will become different from zero only if the associated constraints in the primal problem are binding.

The consequences of the complementary slackness optimality conditions theorem in equations (5a) and (5d) is especially relevant in understanding how nodal prices can be used to evaluate system performance.

Note that the complementary slackness optimality conditions are a particular case of the Karush-Kuhn-Tucker optimality conditions used in constrained optimization, since it is pertinent to say that linear programming is a particular case of constrained optimization.

Now consider a real number π_k associated to each node *k*. π_k is called the potential of node *k*. Now we can define the reduced cost c_{ij}^{π} of an arc (*i, j*) as $c_{ij}^{\pi} = c_{ij} - \pi_i + \eta_{ij} \cdot \pi_j$

The generalized flow optimality conditions theorem [Ahuja et al., 1993] states that a flow vector $\mathbf{e}^*$ is an optimal solution of the generalized minimum cost flow problem if it is feasible and for some vector π of node potentials, the following conditions are met:

(a) If $0 < e_{ij}^* < e_{ij,\max}$, then $c_{ij}^{\pi} = 0$

(b) If $e_{ij}^* = 0$, then $c_{ij}^{\pi} \geq 0$

(c) If $e_{ij}^* = e_{ij,\max}$, then $c_{ij}^{\pi} \leq 0$

Now, let d_k denote the shortest path distance from the source node to the node *k* in the residual network *G* ($\mathbf{e}^*$), using c_{ij} as arc lengths. The shortest path optimality conditions imply that $d_j \leq d_i + c_{ij}$. If $\eta_{ij} \leq 1$, it also implies that, $\eta_{ij} \cdot d_j \leq d_i + c_{ij}$.

Now consider the node potential to be equal to the negative of the distance ($\pi_k = -d_k$). Then we can rewrite the shortest path optimality condition as

$$c_{ij}^{\pi} = c_{ij} - \pi_i + \eta_{ij} \cdot \pi_j \geq 0$$

According to the generalized flow optimality conditions theorem stated before, π is an optimal set of node potentials (note that if the costs are all more or equal than 0, the potentials are all less or equal than 0).

Now, by setting $\pi_k = \lambda_k, \forall k \in N$ and $\delta_{ij} = \mu_{ij} = 0, \forall (i, j) \in A$, we have also an optimal solution of the dual problem. Using this particular set of potentials, we get:

(a) If $0 < e_{ij}^* \leq e_{ij,\max}$, then $c_{ij}^{\pi} = 0$

(b) If $e_{ij}^{*}=0$, then $c_{ij}^{\pi}\geq 0$

Therefore, the necessary conditions are met and the generalized flow optimality conditions theorem is satisfied. From a different point of view, it is easy to realize that this set of dual variables also satisfies the complementary slackness conditions and according to the complementary slackness optimality conditions theorem, it is an optimal solution to the dual problem.

In conclusion, in a lossless network ($\eta_{ij}=1, \forall(i,j)\in A$) the nodal prices $\lambda_k, \forall k \in N$ for the optimal flow $\mathbf{e}^*$ are simply the distance labels calculated by solving the shortest path problem in the residual network $G(\mathbf{e}^*)$ using $-c_{ij}$ as arc lengths

If the network is generalized (unrestricted η_{ij}), given the nodal price in an arbitrary node the rest of the nodal prices can be calculated similarly by recursively using the equation $c_{ij}^{\pi}=c_{ij}-\pi_i+\eta_{ij}\cdot\pi_j=0$ in the augmented forest structure[2] associated to the residual network.

4.4 Sensitivity analysis in the GMCFP

In this section it is assumed that the capacities are integer numbers. If they were not, it is always possible to transform the network into one with integer capacities. The sensitivity analysis is carried out in a lossless network ($\eta_{ij}=1, \forall(i,j)\in A$). Similar results probably apply to generalized networks, but the reasoning in generalized networks is considerably more cumbersome so it will be omitted.

The analysis presented in Section 4.3 is especially relevant to understand how flows, arc capacities, and nodal prices relate, and allow us to establish a relationship between the changes in the parameters in the network and the solutions of the primal and dual problems. It will explain the changes that should be expected in the optimal solution

[2] See [Ahuja et al., 1993] for a definition of augmented forest.

of the GMCFP resulting from changes in the demand and/or changes in the capacities in one or more of the arcs.

4.4.1 Demand sensitivity analysis

First, we need to enunciate the following lemma: Suppose that a flow vector $\mathbf{e}^*$ satisfies the reduced cost optimality conditions (a particular case of the generalized flow optimality conditions with $\eta_{ij} = 1, \forall (i, j) \in A$) and we obtain $\mathbf{e}^\#$ from $\mathbf{e}^*$ by sending flow along a shortest path from s to other node. Then, $\mathbf{e}^\#$ also satisfies the reduced cost optimality conditions [Ahuja et al., 1993].

For this section, assume that a flow vector $\mathbf{e}^*$ is optimal for the network *G*, and that G ($\mathbf{e}^*$) is the residual network using c_{ij} as arc lengths. Then, suppose that the demand in a node *k* becomes $b_k + 1$.

4.4.1.1 Changes in the flow vector

If we augment 1 unit of flow from the source node *s* to the node *k* along the shortest path ς_{sk} in the residual network G ($\mathbf{e}^*$) using c_{ij} as arc lengths, the lemma stated previously implies that the new flow vector $\mathbf{e}^\#$ is optimal for the modified minimum cost flow problem. If there is no directed path from the source node to node *k* in the residual network G ($\mathbf{e}^*$), the problem becomes infeasible (not enough system capacity to satisfy the demand).

4.4.1.2 Changes in the objective function value

The extra unit of flow from the source node to the node *k* along the shortest path ς_{sk} will change the value of the objective function by $\sum_{(i,j)\in\varsigma_{sk}} c_{ij}$ units.

4.4.1.3 Changes in the nodal prices

If the residual capacity before the demand increases is more than 1 in all the arcs between the source node *s* and the node *k* along the shortest path ς_{sk}, no arcs become congested, the residual network does not change, the node potentials do not change, the reduced costs do not change, and therefore the nodal prices do not change either.

If the residual capacity before the demand increases is equal to 1 in one or more of the arcs between the source node *s* and the node *k* along the shortest path ς_{sk}, their new residual capacity will become 0 due to the extra flow, the respective arcs will disappear from the residual network, and therefore the solution to the shortest path problem in the new residual network will now be different than before. Therefore, nodes located downstream of the now congested arcs will see an increase in their nodal prices as a result.

Note that no previously congested arcs (with $r_{pq} = 0$) can be in the shortest path ς_{sk}, therefore they are not directly affected by the increase in demand.

4.4.2 Arc capacity sensitivity analysis

For this section, assume that a flow vector $\mathbf{e}^*$ is optimal for the network *G*, and that $G\ (\mathbf{e}^*)$ is the residual network using c_{ij} as arc lengths. Then, suppose that the capacity of an arc (*p, q*) decreases to $e_{pq,\max} - 1$.

4.4.2.1 Changes in the flow vector

If the residual capacity in the arc ($r_{pq} = e_{pq,\max} - e_{pq} + e_{qp}$) is equal or more than 1, $\mathbf{e}^*$ is still feasible and nothing changes. Now, if $r_{pq} = 0$, an excess of 1 is created at node *p* and a deficit of 1 is created at node *q*. To solve the imbalance, we send 1 unit of flow from node *p* to node *q* along the shortest path ς_{pq} in the residual network $G\ (\mathbf{e}^*)$ using c_{ij} as arc lengths. If the residual network $G\ (\mathbf{e}^*)$ contains no directed path from node *i* to node *j*, the problem becomes infeasible (not enough system capacity to satisfy the demand).

4.4.2.2 Changes in the objective function value

If the residual capacity in the arc r_{pq} is equal or more than 1, the objective function does not change. But if the residual capacity in the arc r_{pq} is 0, then the reduction in the capacity of the arc will change the value of the objective function. First, it will cause a reduction of c_{pq} in the objective function value because of the reduction in the flow through arc (*p, q*). Second, it will cause an increase of $\sum_{(i,j)\in\varsigma_{pq}} c_{ij}$ in the objective function value because of the increase in the flow along the shortest path ς_{pq}.

Therefore, the total change in the objective function value is $\sum_{(i,j)\in\varsigma_{pq}} c_{ij} - c_{pq}$ units. Since the flow vector $\mathbf{e}^*$ was optimal, and in the original network (p, q) was the shortest path from node p to node q, the objective function value increases or remains equal when a capacity decrease occurs in any of the arcs.

4.4.2.3 Changes in the nodal prices

First, let assume that the residual capacity in the arc r_{pq} before the capacity change is more than 1. Then, if the capacity in the arc (p, q) decreases by 1 unit, the flow will not change, and neither will change the residual network, the node potentials, the reduced costs, nor the nodal prices.

If the residual capacity in the arc r_{pq} before the capacity change is equal to 1, the optimal flow vector $\mathbf{e}^*$ does not change with the arc capacity change. However, since r_{pq} becomes 0 after the capacity decrease, the arc will disappear from the residual network and therefore the solution to the shortest path problem in the new residual network using c_{ij} as arc lengths will now be different than before. Therefore, the nodes located downstream of node *p* will see an increase in their nodal prices as a result.

If the residual capacity in the arc r_{pq} before the capacity change is 0, an excess of 1 is created at node *p* and a deficit of 1 is created at node *q*. To solve the imbalance, we send 1 unit of flow from node p to node q along the shortest path ς_{pq} in the residual network $G(\mathbf{e}^*)$ using c_{ij} as arc lengths. If the residual capacities along the shortest path ς_{pq} remain positive despite the increase in flow, the nodal prices do not change. However, if one or more residual capacities along the shortest path ς_{pq} become 0 as a consequence of the increase in flow through the arc, the arc will disappear from the residual network and therefore the solution to the shortest path problem in the new residual network will now be different than before. Therefore, nodal prices will increase as a result.

4.5 Generalized maximum flow problem

The maximum total feasible flow is the maximum flow that a network is able to transport from a source node s to a sink node t. In the maximum flow problem, we are given a flow network and wish to find the flow that maximizes the value of the total feasible flow. Therefore, the maximum flow problem may be stated as follows: in a capacitated s-t network, we wish to send as much flow as possible between 2 special nodes, a source node s and a sink node t, without exceeding the capacity of any arc. In the generalized maximum flow problem, we also assign an extra parameter to each arc: a gain or efficiency parameter so that there may be gains or losses of flow in the arcs.

According to the max-flow min-cut theorem, in a capacitated lossless s-t network the maximum feasible value of the flow from the source node s to the sink node t is equal to the minimum capacity among all minimal cut-sets [Ahuja et al., 1993], [Ford & Fulkerson, 1956].

Even though a catastrophic event of a magnitude such that the NEES is unable to satisfy the demand is extremely unlikely, there is a direct linkage between congestion in some points of the system and energy prices, as demonstrated in the previous section. In this way, the calculation of the maximum flow that the network may provide the decision makers with a good indicator of the state of the system infrastructure and help them to elaborate contingency plans to avoid conditions harmful to the system. Also, the solution of the GMFP under different scenarios can be used to evaluate the possibility of local congestion in the transportation system.

The GMFP can be mathematically represented as follows:

$$Z = \max\left\{\sum_{\forall k} \underline{e_{kt}}\right\} \qquad (1)$$

subject to:

$$\mathbf{A} \cdot \mathbf{e} = \mathbf{b} \qquad (1b)$$

$$\mathbf{e_{min}} \leq \mathbf{e} \leq \mathbf{e_{max}} \qquad (1c)$$

where $E_{kt}, \forall k$ corresponds to the flows in the arcs going from any node k to the sink node t.

The GMFP will be solved for the NEES network model to identify vulnerabilities in the energy grid, as it will be described in Section 6.4.

4.6 Simulations in the network model

It is well known that linear programming problems can be solved by the very efficient simplex algorithm. Furthermore, if the constraints can be formulated in such a way that each variable appears at the most in 2 equality constraints, once with a coefficient of 1 and the other with a negative coefficient (not necessarily 1), then the problem has a network structure and its computational efficiency can be further improved using the network simplex method, which is considerably faster than the regular simplex method.

The mathematical formulation of the GMCFP in the NEES network model includes a complicating constraint (the total emissions constraint) that breaks the network structure. However, it is certainly possible to decompose the problem so that the nested network problem can be solved as a first step, hence providing a good starting point for solving the complete linear programming problem.

In particular, the CPLEX software [CPLEX, 1998] recognizes the embedded network structure automatically, solves the network portion of the problem using the network simplex algorithm, and then performs standard linear programming iterations on the full problem using the network solution as an advanced starting point. For problems with few complicating constraints (such is the case of the integrated energy system), the advanced basis can be a very good approximation of the optimal solution of the problem, and so it can greatly improve the performance of the simplex method [Bride & Mamer, 1977], [Bride, 1985], [Hsu, 1996]. The computational results presented in [Gulpiner et al., 2002] show that looking for an embedded network can be an effective procedure for creating an advanced basis even for general classes of linear programming problems.

5 Reliability in the NEES

Assessment of the NEES reliability is very important in order to evaluate conditions that may result to be harmful to the US energy grid operation, to discover where the system is more vulnerable, or to recognize ways to improve the performance of the system under different operating conditions.

This chapter is made up of three sections. Section 5.1, *Reliability and disruptions*, provides a background to understand reliability in the context of the NEES. Section 5.2, *Congestion, reliability, and nodal prices*, further discusses the relationship existing among these three elements, discussion based on the analytical evidence provided in Chapter 4. Section 5.3, *Impacts of hurricanes Katrina and Rita in the NEES*, is devoted to present the highlights and main conclusions of a data collection effort following hurricanes Katrina and Rita in 2005. The revision of the effects of hurricanes Katrina and Rita in the NEES is used as a case study for improving understanding of reliability in the NEES. Data related to changes in the network parameters due to the hurricanes is also presented in this section.

5.1 Reliability and disruptions

We may consider reliability, generally speaking, as a measure of the performance of a device or system. In particular, power system reliability can be defined as the degree to which the performance of the system results in electricity being delivered to costumers within accepted standards and in the amount desired [Ringlee et al., 1993]. A related definition is the one given by NERC for power system adequacy: "*the ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements*" [NERC, 2006]. These definitions, made in the context of electric generation, transmission, and distribution, can be extended to the NEES if we consider a broadly defined electric system that also includes the fuel transportation networks.

Disruptions in the energy system are found in supply, transportation, storage, and end-use, and they may be divided into 4 rough categories: (1) Natural causes (e.g. hurricanes, temperature extremes, drought, earthquakes, ice, landslides), (2) Primary equipment failure due to accidents, wear out, or terrorist activities (e.g., circuit faults, generator forced outages, pipeline ruptures, and railway disruptions), (3) Labor unavailability (e.g., strikes of unionized rail or coal mine workers, unavailability of pilots in the Mississippi river after hurricane Katrina), and (4) Communication failures. Also, perception has grown that the NEES, including the fuel supply system, given its role as a critical national infrastructure, may be more exposed to high-severity contingencies as result of intentional acts [Salmeron et al, 2004].

Disruptions or degradation in the performance of one or more of the facilities represented in the NEES model might have effects that can be perceived in other parts of the system as price increases and energy supply problems. Henceforth, a disruptive event will be understood as a significant reduction in the capacity of one or more facilities in the NEES, and will be reproduced in the network model as a reduction in the arcs representing those facilities.

5.2 Congestion, reliability, and nodal prices

5.2.1 Congestion and nodal prices

Congestion is usually defined as a condition in a transportation system when a binding limit on the system's transfer capability is reached. In electric power systems, congestion occurs when physical constraints on the transmission system make it impossible to transmit power between two different buses. This idea can be extended to the NEES network model, by saying that congestion occurs when the upper bound constraints for an arc (i, j) is binding. That is, the flow in the arc has reached its maximum capacity and any extra flow going to node j will need to follow a different path.

Two main causes for congestion come immediately to mind: high demand and reductions in arc capacities. From the point of view of the optimization problem, the addition of constraints or the tightening of existing ones (for example the reduction in the capacity in one or more arcs) will increase congestion and therefore the total operation cost, and in general will drive the nodal prices up.

In Section 4.4.1, the effect of increasing the demand on nodal prices was explored using duality theory. The results presented there are summarized in what follows (for the complete proof, see Chapter 4). Assuming that the network is operating with an optimal flow vector $\mathbf{e}^*$ in a GMCFP context, if the demand in a node k increases by Δ, one of the following will happen:

(a) If $r_{pq} > \Delta$ for all the arcs along the shortest path ς_{sk} in the residual network $G(\mathbf{e}^*)$, the flow along the path ς_{sk} will increase by Δ, the objective function will increase by $\sum_{(i,j)\in\varsigma_{sk}} c_{ij}$, and the nodal prices will remain the same. The problem remains feasible.

(b) If $r_{pq} = \Delta$ in any of the arcs along the shortest path ς_{sk} in the residual network $G(\mathbf{e}^*)$ and $r_{pq} > \Delta$ in the others, the flow along the path will increase by Δ, the objective function will increase by $\sum_{(i,j)\in\varsigma_{sk}} c_{ij}$, but the new congestion in the arc (*p, q*) will cause an increase in the nodal prices downstream node *p*. The problem remains feasible.

(c) If $r_{pq} < \Delta$ in one (or more) of the arcs along the shortest path ς_{sk} in the residual network $G(\mathbf{e}^*)$, the flows will increase not only along the shortest path ς_{sk}, the objective function value will increase (or remain the same if the arc costs where the flow increase are 0), the increase of flows may cause congestion in other arcs, and the nodal prices will in different nodes. The problem may become infeasible.

In other words, increases in the demand imply the use of more expensive paths to send energy from where it is produced to where it is consumed once the cheaper paths start experiencing congestion, increasing prices in different parts of the system.

In Section 4.4.2, the effect of tightening capacity on nodal prices was explored using duality theory. The results presented there are summarized in what follows (for the complete proof, see Chapter 4). Assuming that the network is operating with an optimal flow vector $\mathbf{e}^*$ in a GMCFP context, if the capacity of an arc (p, q) decreases by Δ, one the following will happen:

(a) If $r_{pq} > \Delta$, the flow, the objective function, and the nodal prices will remain the same. The problem remains feasible.

(b) If $r_{pq} = \Delta$, the flow vector and the objective function value will remain the same, but the new congestion in the arc will cause an increase in the nodal prices downstream node p. The problem remains feasible.

(c) If $r_{pq} < \Delta$, the optimal flow vector will change, the objective function value will increase or remain the same, and the redistribution of flows may cause congestion in other arcs upstream as well increasing nodal prices in many different nodes. The problem may become infeasible.

In other words, a disruption in the facilities represented by a given arc (reduction in the arc capacity) implies the re-accommodation of the energy flows which will drive the system operation away from the optimal (in terms of minimal operation cost) pre-contingency operation.

5.2.2 Congestion and reliability

Congestion implies facilities working at full capacity. In the particular case of transmission lines, that implies that they operate at or very close to their nominal capacity, which imply operation at a higher temperature, thermal expansion, shorter distances to ground, and therefore a higher probability of failure. If a failure in a line occurs, the energy going through that line will need to be redistributed to other transmission lines that in turn might become congested, increasing even further the probability of failure in other transmission lines. Congestion in the electric transmission system is also directly related to stability problems. If the proper corrective measures are not taken in time, consequences of congestion may lead to cascading failures such as the blackout occurring in August 14th 2003 in the Northeast. Among others, one of the possible measures to correct serious congestion problems and improve system reliability is load shedding, that is, a forced reduction of the demand by disconnecting non-critical load. The same relationship between congestion and reliability happening in the electric subsystem also exists, with their own particularities, in the natural gas and coal subsystems.

As explained in the previous section, a disruption in a facility located in an arc that is not congested may not cause, depending on the size of the facility, any negative effect in the total operation cost, in energy prices, nor in the availability of energy supply. On the other hand, a disruption in a facility located in an arc presenting congestion may increase the total operation cost and energy prices and maybe supply problems to satisfy the energy demand.

Nodal prices obtained from the dual solution of the GMCFP can be used to evaluate the effects of congestion and improve system reliability. With this in mind, Chapter 6 will introduce some metrics based on nodal prices to evaluate the effects of system disruptions and to assess in capacity expansion investments.

5.3 Impacts of hurricanes Katrina and Rita in the NEES

5.3.1 Overview

Catastrophic events like the 2005 hurricanes in the Gulf of Mexico (GOM) area encompass not only dramatic cost in terms of human lives, but also a devastating effect in critical national infrastructure. The energy infrastructure located in the affected zones has fundamental importance in terms of the operation and performance of the NEES, which comprises the production, transportation, storage, and conversion of electricity, coal, and natural gas, among others. The coal and natural gas production and transportation subsystems share with electricity the common characteristic that they can be moved in bulk quantities via a transportation network from the source of their production to the site of their use. These different transportation networks are highly coupled, and it is mainly through the electricity subsystem that these couplings take place.

The lessons learned after Katrina hit ground in August 29th 2005 can help to obtain a better understanding of the impact of catastrophic events in the energy system, to appreciate how events propagate geographically and in time, and to study infrastructure interdependencies. Acquiring such knowledge can be also very helpful in order to help prevent the most harmful effects of catastrophic events, to raise awareness about infrastructure vulnerabilities, and to improve the government and industry reaction capacity in the aftermath of catastrophic events.

This section summarizes a data gathering effort performed following Hurricane Katrina to characterize the effects of the 2005 hurricanes on the U.S. bulk energy transportation system [McCalley & Gil, 2006]. Data was gathered for the electric, natural gas, and coal bulk production and transportation sub-systems, since these are the main energy systems incorporated into the simulation tools associated to our NEES model. The data reflects the hurricane's effects in terms of changes in production, transportation, storage, and prices of different energy forms. Where possible, data was gathered to reflect conditions given months or years before and for the months following the hurricanes. Data sources include daily situation reports by the Department of Energy's Office of Electricity Delivery and Energy Reliability (OE), Energy Information Administration (EIA), Louisiana Public Services Commission, North America Electric Reliability Council (NERC), Mineral Management Service (MMS), Office of Pipeline Safety (OPS), Pipeline and Hazardous Materials Safety Administration (PHMSA), and on-site interviews, news releases, and financial releases offered by energy companies affected by the hurricanes, among others.

The main motivation behind this data collection effort is to obtain data for use in validating the simulation tools associated to our NEES model. It is also expected that this data will be useful in understanding the nation's bulk energy transportation systems during extreme events.

The most noticeable interdependency between energy subsystems was the impact of high natural gas prices as a consequence of the hurricanes on the coal and electric subsystems. Through price and availability of natural gas, the effects of the disruptions permeated and propagated to the coal and electric subsystems.

From the observation of the data collected we believe that, despite the magnitude of the event, the bulk energy system behaved within reasonable limits. From a reliability standpoint, the bulk energy system seems to be pretty robust, and able to tolerate large and multiple disruptions. An important factor helping with this robustness is coal storage, that can dampen the negative effects caused by disruptions in infrastructure of the U.S. energy system.

5.3.2 Effects on the electric sub-system

This section summarizes hurricanes Katrina and Rita's effects in terms of damage to electric generation, transmission, and distribution facilities, and the restoration efforts carried out by the affected electric power utilities.

Transmission and distribution facilities in areas affected by the hurricanes sustained heavy damage. Since in general electric transmission and distribution facilities are very exposed to the elements, natural event like hurricanes will likely cause a temporary electric load reduction because of the damage in transmission and distribution equipment. As a consequence, even though some electric generating facilities were affected by the hurricanes, the damage in transmission equipment and the virtual destruction of the distribution systems in the area affected by Hurricane Katrina caused a forced reduction of electric load, and therefore no generation shortage could be perceived. It is interesting to notice that even though some electric generating facilities were affected by the hurricanes, the forced decrease in electric load (as a result of the widespread damage to transmission and distribution systems) enabled the affected companies to declare that there was no generation shortage.

The previous observation is interesting in regards to our modeling of catastrophic events affecting the NEES. From the evidence collected to this point, the most appropriate way to model the impact of the hurricanes in the electricity component of the NEES structural model is by reducing the electrical demand in the transshipment nodes corresponding to the affected areas. In particular, it is pertinent to adjust the electrical demand in the EES and ERCOT nodes. Also, some minor adjustment may also be necessary to adjust the capacity of the arcs representing generation, but this adjustment does not seem to be critical, given the small size of most of the units out of service and the short period that the larger units remained off-line (in particular Waterford). Adjustments on the capacity of the arcs representing transmission capability between different regions (transshipment nodes) do not seem to be necessary.

Finally, electric prices can be used as a good indicator of how the destructive effects of hurricane Katrina in other subsystems (specially the natural gas production and transportation system) affected the electric system nationwide, and to better understand interdependencies between different subsystems. In the same lines, actual electricity prices can be compared to nodal prices obtained by simulation in the NEES network model for the sake of validation of the model, as it will be presented in Chapter 7.

5.3.3 Effects in the natural gas sub-system

This section summarizes hurricanes Katrina and Rita’s effects in terms of damage to natural gas production, transportation, and processing facilities.

Natural gas production in the Gulf of Mexico and Texas corresponds approximately to 50% of the total US production. Therefore, due to the relative importance of natural gas production in the area in terms of the total national production, it is not a surprise that a spike in prices of natural gas could be observed nationwide as a result of the natural gas productive capacity reduction in the Gulf of Mexico, and that the effects of this price increase permeated to the coal and electricity subsystems as well. At the peak of the Hurricane Katrina, a recorded 88% of daily gas production in the GOM was shut-in[3], and approximately 80% of the natural gas was shut-in after Rita. By the end of 2005 approximately 20% of the natural gas production capacity in the GOM remained shut-in. Figure 5.1 illustrated the natural gas production by state.

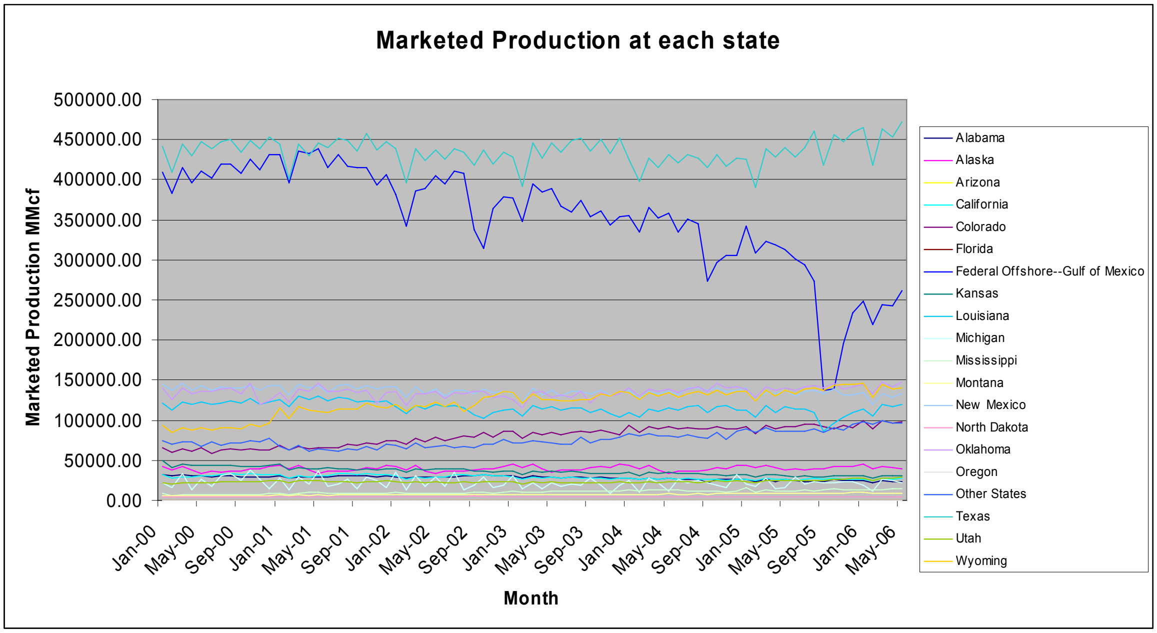

Figure 5.1. Natural gas marketed production at each state

Several natural gas gathering pipelines and processing plants in the area suffered disruptions or limitations on their normal operations, mainly due to heavy rains and floods caused by the hurricanes. Bulk natural gas transportation was hit hard as well. As seen in Figures 5.2 and 5.3, the number of disruptions in natural gas pipelines increased dramatically due to the hurricanes with respect to other periods, especially due to heavy rains and floods. These changes in natural gas production and transportation capacity are of extreme importance for an adequate modeling of the event in the NEES network model.

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[3] The shut-in of gas is a standard safety procedure in which the valves on a well are closed so it stops producing. Once the facility is inspected and the problems solved, the facility can then be brought back on line.

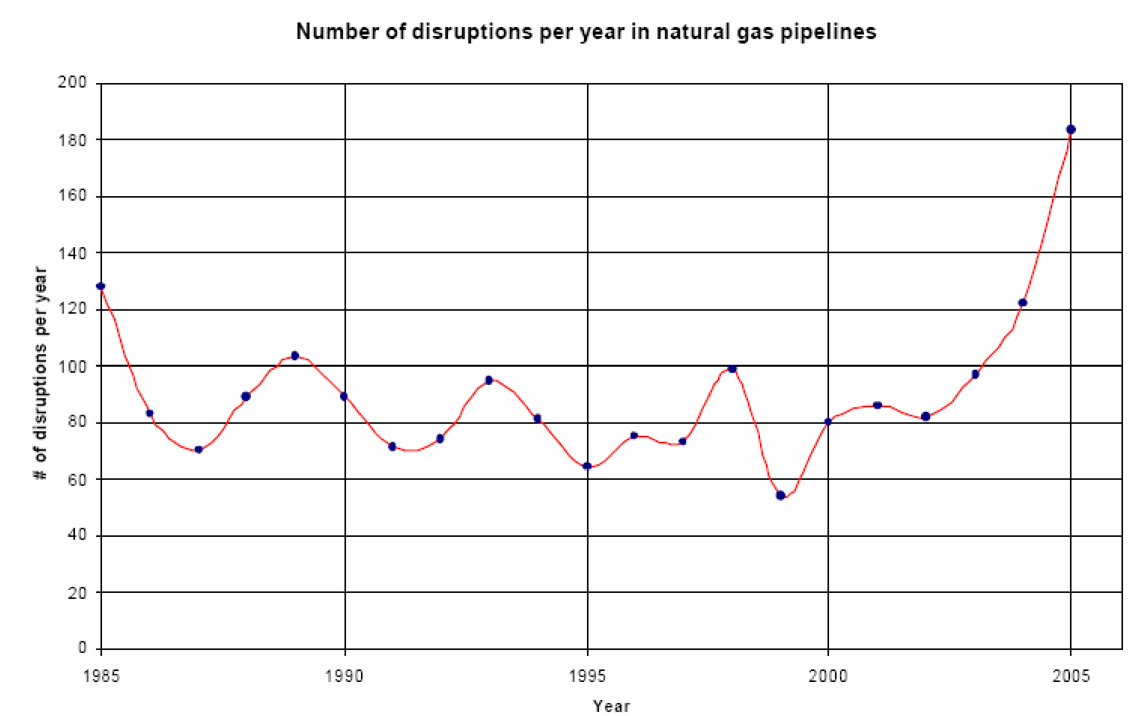

Figure 5.2. Number of disruptions per year in NG pipelines in the U.S.

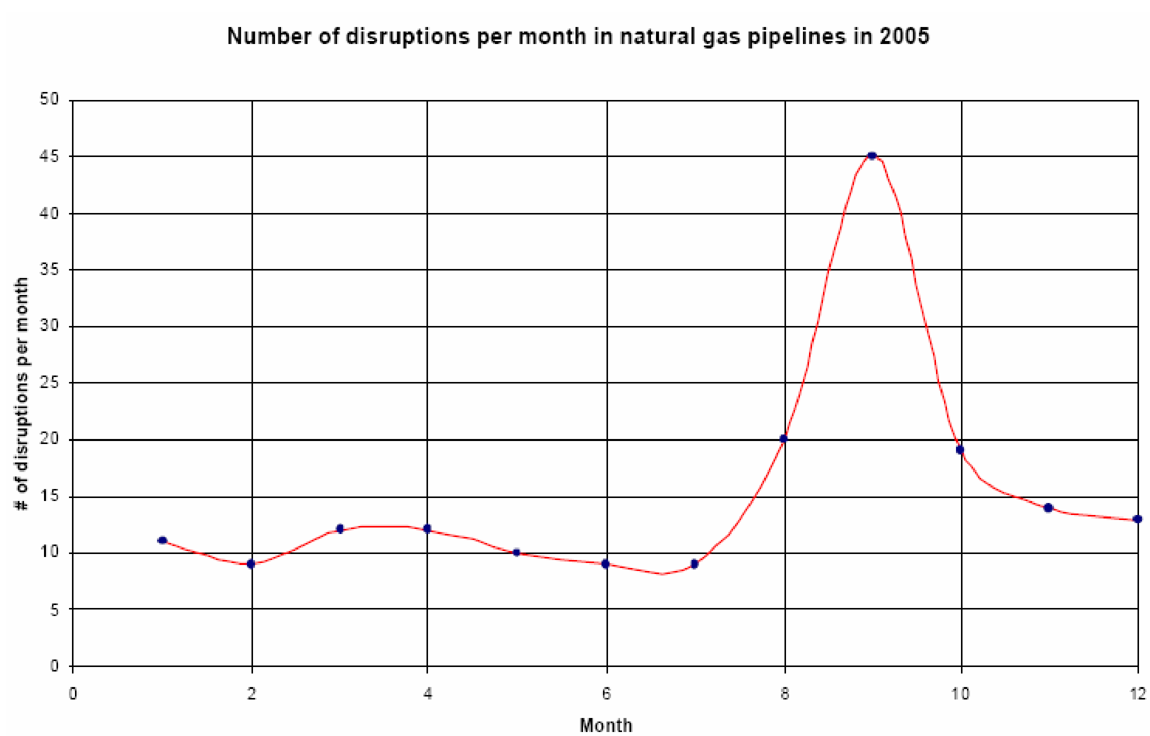

Figure 5.3. Number of disruptions per month in NG pipelines in the U.S during 2005

An interesting situation can be observed in the natural gas storage. Due to the shortage in natural gas production and the transportation problems, it was expected to see some depletion of the natural gas in underground storage. However, it seems that the natural gas consumption decreased due to the high prices, and therefore at the end of the winter the storage levels were even higher than in previous years. This observation suggests us to consider an elastic natural gas demand in our model.

Due to the magnitude of the disruption and to their relative weight at the national level, changes in natural gas production and transportation capacity caused by Katrina seem to be of the utmost importance for an adequate modeling of the event in the NEES network model. Particularly, the capacities of arcs representing natural gas production in the Gulf of Mexico, in Louisiana and Arkansas, and in Texas need to be adjusted accordingly for the months after the hurricanes. All of these arcs link to the natural gas transshipment node corresponding to the region (Southwest node). The capacity of the arc representing natural gas production in Mississippi and Alabama (connecting to the Southeast transshipment node) also needs to be adjusted. Moreover, in order to appropriately model the impact of hurricanes Katrina and Rita to natural gas pipelines, capacities of arcs connecting different natural gas transshipment nodes needs to be adjusted. In particular, the affected transmission arcs in the NEES model are: Southwest-Central, Southwest-Western, and Southwest-Southeast. The most important of these is the Southwest-Southeast arc, in view of the fact that according to previous simulations performed using the NEES network model this arc operates at maximum capacity. Operation at maximum capacity (a binding upper bound) is associated with congestion in the natural gas flow going from Southwest to Southeast. Therefore, any reduction of the capacity of this arc will lead to an increase in the marginal prices in other nodes of the system. This assertion is further confirmed by analyzing natural gas price spikes in different parts of the system following the hurricanes.

As previously mentioned, a significant increase in natural gas prices could be observed after Hurricane Katrina. Natural gas marginal prices at different nodes can be used as an indicator of how the effects of the hurricanes propagated through the system. Also, actual natural gas prices can be compared to nodal prices obtained by simulation in the NEES network model for the sake of validation of the model, as will be presented in Chapter 7.

5.3.4 Effects in the coal sub-system

This section summarizes hurricanes Katrina and Rita's effects in coal production, transportation, storage levels, and price. Even tough there were no major damages of the hurricanes to coal facilities (coal mines in the area are not close to the coast), there was a suspicion that the patterns of coal production and transportation may have been altered as a result of coal being a substitute fuel for natural gas in what refers to electricity generation.

From the coal data collected, we can say that no significant coal production facilities were affected by the hurricanes. Despite the fact that some coal transportation facilities sustained heavy damage as a consequence of Hurricane Katrina, it seems that overall the effects in the coal subsystem were short-lived and almost negligible, if any. The robustness of the coal subsystem is probably due to the leverage offered by the large coal storage stocks and by the possibility of using alternative transportation paths.

It seems that during the Fall months following Katrina, the coal stocks did not recover as usual, probably because the high natural gas prices motivated a shift to cheaper coal-fired generation. However, due to the fact that the large amount of coal in storage by the electric sector acts as a buffer, the impact was apparently not poured out to coal production. Coal prices only increased noticeably after January 2006, probably because coal storage levels in the electric sector had reached a low threshold after the slow recovery of the storage levels in the Fall and subsequent higher consumption during the Winter months. The attempt by the electric power companies to maintain their coal storage at a reasonable size might have motivated this price increase.

Also affecting the coal storage levels and its price was the disruption of coal shipments from the mines located in the Powder River Basin (PRB) in Wyoming. In May 2005, two major train derailments shed to light the immediate need for major maintenance on the PRB rail lines, which disrupted rail traffic flows and resulted in a shortfall in rail shipments, as much as 15 percent below the normal level throughout the entire second half of 2005, and to a lesser extent into 2006 [EIA, 2006a].

At this point, no changes in the capacities of the arcs of the coal component of the NEES network model seem to be necessary. The data collected about coal price will prove to be useful when compared with simulation results of the NEES network model for validation purposes.

6 Metrics for assessment of congestion and reliability

Congestion and reliability are notions of utmost importance in the context of the NEES operation, but they may be difficult to take beyond the conceptual level without the help of quantitative metrics for their assessment. We have seen in previous chapters how nodal prices are directly associated to congestion (Section 5.2.1), and how congestion is related to reliability (Section 5.2.2). Thus, nodal prices may be used as a foundation stone to build metrics able to capture the essence of the congestion and reliability traits. Nodal price-based metrics that quantify congestion and reliability are developed in this chapter with two objectives in mind: 1) evaluating impact of disruptions and 2) assessing capacity expansion projects. Evaluating the severity of disruptions at different locations can be useful to understand how its effects propagate geographically and in time, in order to provide insight in infrastructure interdependencies that may become observable only under the effects of a perturbation. Capacity expansions in NEES infrastructure can be of great help in order to reduce congestion and improve reliability, and the optimal allocation of new resources is a task that can be informed by metrics based on nodal prices. Note that both types of assessments, evaluating disruption severity and developing capacity expansion plans, are related to how the network variables change as a result of a change in the capacity of one or more of the arcs in the NEES network model.

This chapter is organized as follows: Section 6.1, *Use of dual variables in metrics for the assessment of congestion and reliability*, describes how nodal prices have been used in the context of electricity markets and suggests their use as metrics in the NEES. Section 6.2, *Evaluating the impact of disruptions*, proposes a measure to evaluate the severity of a contingency. Section 6.3, *Metrics for capacity expansion assessment*, introduces a metric based on nodal prices for the assessment of investments in capacity expansion. Section 6.4, *Vulnerability assessment*, presents an algorithm based on network flow theory to identify where the system is more vulnerable in terms of the overall system transportation capacity.

6.1 Use of dual variables in metrics for the assessment of congestion and reliability

Solution of the GMCFP provides a primal and a dual solution, as explained in Chapter 4. While the primal solution consists of the flows in the arcs, the dual solution consists mainly of 2 sets of values: 1) the nodal prices associated with the equality constraints in the primal problem (conservation of flow in the nodes) and 2) the reduced costs associated to the inequality constraints in the primal problem (capacity constraints in the arcs). As defined in Section 4.3.2, the reduced costs can be directly calculated as a function of the nodal prices and the network parameters as $c_{ij}^{\pi} = c_{ij} - \pi_i + \eta_{ij} \cdot \pi_j$. Note that while the nodal prices are associated with the nodes, the reduced costs are associated with the arcs in the network formulation.

A nodal price can be understood as the change in objective function of sending one extra unit of flow to the respective node. If the objective is to minimize cost, as discussed in Chapter 4, the nodal price represents the value of energy at the node, including the cost of the energy itself and the cost of delivering it to that location.

Differences in nodal prices between 2 different nodes (and therefore reduced costs) can be explained by the presence of losses and/or congestion. Nodal prices are able to adequately capture variations from node to node due to any of these elements, which is the reason why their use as a pricing mechanism has grown more and more familiar within the electric power industry.

Electricity markets have been using the information from nodal prices, called Locational Marginal Prices (LMP) in this context, to improve the efficient usage of the power grid, to perform congestion management, and also to design a pricing structure for the power sector [Schweppe et al., 1988]. Since LMPs are equal to the marginal valuation of net benefits in the network at different locations, they provide the right incentives for consumption and generation decisions, both in the short run and in the long run [Oren et al., 1995]. Moreover, the standard market design proposed by the Federal Energy

Regulatory Commission (FERC) in 2002 incorporates a LMP mechanism to induce efficient electric power markets [Sun, 2002].

In the NEES network model, the electricity, coal, and natural gas subsystems are analyzed together in a single integrated mathematical framework for the primary energy production, transportation, and storage, and for the electric energy generation and bulk transmission. Since the GMCFP simulation in this context provides not only the optimal energy flows (variables in the primal problem formulation) but also the optimal nodal prices (variables in the dual problem formulation), we extend the application of LMPs to the integrated energy system.

As in the electricity subsystem LMPs are expected to induce efficient electric power market practices, it is reasonable to also expect nodal prices will do the same in the other subsystems. Furthermore, by exploring the nodal prices obtained in the solution of the GMCFP we have tools to analyze interdependencies (as defined in Section 6.2) between the different facilities represented in the NEES and to better understand how changes in one location will affect other parts of the system.

In the network model, the usage of nodal prices or reduced costs for the assessment of congestion and reliability will depend on the nature of the assessment and on who is making the decisions. While a centralized decision maker interest will focus on the effects of changes in the network on total cost reduction and on nodal price variability, individual market agents will be more interested in the effects that such changes in the network have on its profits as represented by the changes in nodal price at the particular nodes where they sell or buy energy.

6.2 Evaluating the impact of disruptions

In [Rinaldi et al., 2001], interdependence is defined as "*a bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other*". In the context of the NEES network model, the state of a node could be defined by its nodal price, obtained from the optimal solution of the GMCFP. Therefore, we can define the interdependence between two nodes as the relationship through which the nodal price in one node influences or is correlated to the nodal price in the other. The interdependence between two arcs can be defined in a similar way, but considering that the state of an arc is defined by its reduced cost.

Interdependencies are hard to notice under normal operating conditions. When a major perturbation strikes the system, these interdependencies are likely to be revealed through changes in normal energy prices and flows. Metrics to evaluate the impact of disruptions in the NEES are essential in studying how the effects of a disruption propagate geographically and in time, to adequately comprehend the interdependencies and dynamics of the energy system, and to recognize the essential infrastructure that, if disrupted, may adversely affect the performance of other infrastructure.

Hereafter, a disruption is understood as a forced reduction in the capacity of one or more facilities in the NEES, and can be represented in the NEES network model as a reduction in the capacity of the arcs corresponding to those facilities. As explained in Chapters 4 and 5, the reduction in the capacity of one or more of the arcs will redistribute the energy flows, increase (or leave the same) the total cost, and drive up (or leave the same) the nodal prices.

A simple metric for the impact of a disruption in the NEES as a whole can be easily obtained by calculating the difference in the total cost (objective function value) of the CPLEX solution of the GMCFP with and without the disruption. But it is the case that, due to regional congestion, prices may spike over acceptable levels in certain parts of the system while remaining similar or the same in other parts. Thus, an aggregated metric for all the NEES may wash out the impact of the disruption in some specific nodes. To correct this, we can also calculate localized indicators of the severity of the event in the different system nodes based on the difference in nodal prices with and without the disruption. Thus, a metric to measure the impact of a contingency in different nodes can be obtained by calculating the difference between the nodal price curves in time with and without the disruptive event, as illustrated in Figure 6.1.

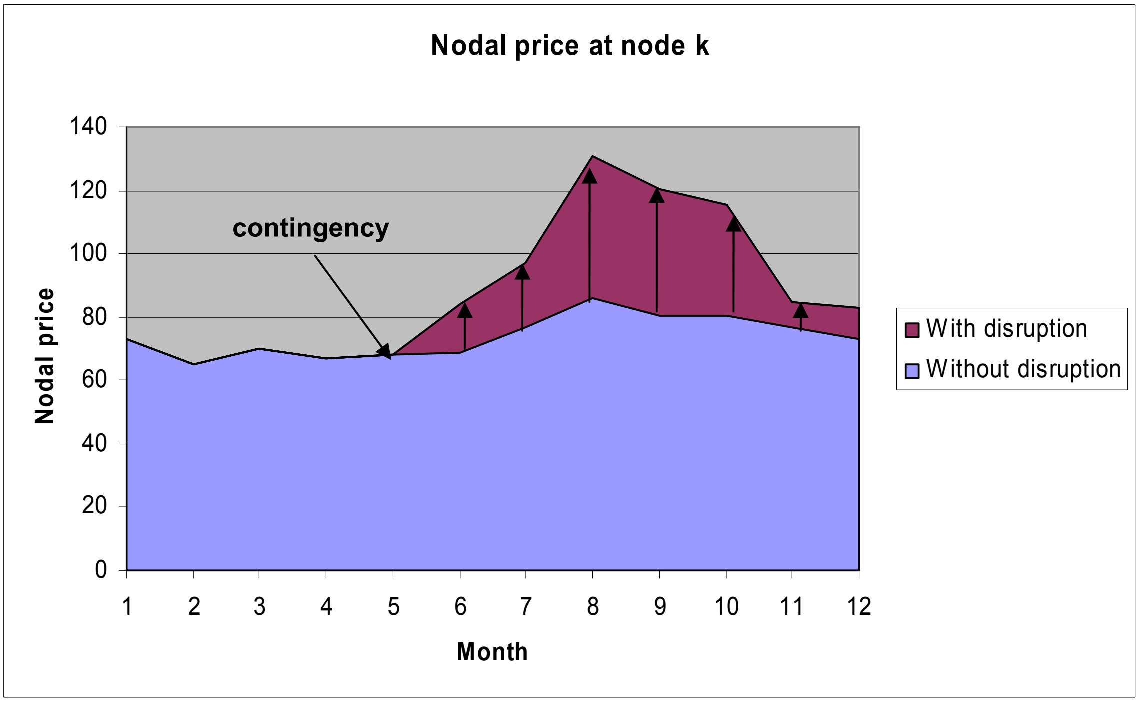

Figure 6.1. Calculation of metric for evaluating impact of disruptions

Although nodal price differences are being proposed for evaluating a specific change in the network parameters (capacity reduction in one or more of the arcs), its use can be extended to analyze other changes in the network parameters, like demand in the nodes or cost in the arcs.

6.3 Metrics for capacity expansion assessment

Hereafter capacity expansion is understood as a project to build new infrastructure (or to expand existing one) in the NEES. A capacity expansion project can be represented in the NEES network model as an increase in the capacity of the corresponding arc, if such arc already existed, or by creating a new capacitated arc, if the arc did not exist.

The merit of a capacity expansion investment can be seen differently through the eyes of an investor than through the eyes of a central planner. In general, the interest of an investor will be focused on maximizing the profit associated with its investment. On the other hand, for a central planner trying to motivate investments, the interest will be focused on improving the system performance through making its operation more economic, reliable, and robust.

From an investor point of view, the main decision criteria for a capacity expansion investment are profit and risk related to its investment[4], assuming that all firms are following rational decision-making and will produce at the profit-maximizing output. The profits or earnings are calculated by subtracting out all costs from revenues.

Revenue is the money that a company collects from customers for the sale of a product or service. In the context of the NEES network model, the revenue can be estimated by using the amount of energy delivered by the facility multiplied by the price at which the energy is finally sold. Assuming that the facility is represented by arc (i, j) in the NEES network model, the energy delivered corresponds to the flow reaching node j ($\eta_{ij} \cdot e_{ij,t}$), and the price of the energy corresponds to the nodal price at the head of the arc ($p_{j,t}$). So in general, the revenue for an arc (i, j) can be calculated as:

$$Revenue_{ij} = \sum_t \eta_{ij} \cdot e_{ij,t} \cdot p_{j,t}$$

For an arc (i, j), the total cost can be estimated by using the amount of energy received by the corresponding facility multiplied by the price at which the energy was bought, plus the cost per unit of flow associated to the facility. Assuming that the facility is represented by arc (i, j) in the NEES network model, the energy received corresponds to the flow leaving node i ($e_{ij,t}$), the energy price corresponds to the nodal price at the tail of the arc ($p_{i,t}$), and the cost per unit of flow correspond to the cost of the arc ($c_{i,j}$). So, the total cost for an arc (i, j) can be calculated as:

$$Cost_{ij} = \sum_t e_{ij,t} \cdot \left(p_{i,t} + c_{ij}\right)$$

[4] A firm is said to be making an economic profit when its average total cost is less than the price of the product at the profit-maximizing output. The economic profit is equal to the quantity output multiplied by the difference between the average total cost and the price. A firm is said to be making a zero economic profit when its marginal revenue equals its marginal cost.

Since the profits correspond to revenues minus all the costs, the profit associated to an arc (i, j) can be calculated as:

$$Profit_{ij} = Revenue_{ij} - Cost_{ij} = \sum_t e_{ij,t} \cdot \left(\eta_{ij} \cdot p_{j,t} - p_{i,t} - c_{ij}\right)$$

In the specific case of the electric transmission system, nodal prices send the right economic signals to the network users concerning the need for reinforcements because of losses and congestion [Pérez-Arriaga et al., 1995], [Oren et al., 1995]. However, a pure marginal network pricing policy (in the form of Financial Transmission Rights[5]) is not able by itself to generate enough revenues to recover the investment cost. This cost recovery problem requires the stipulation of a complementary charge which completes the network marginal revenues. [Rubio-Odériz & Pérez-Arriaga, 2000], [Cameron, 2001]. Several methodologies have been proposed for the allocation of all or part of the existing network cost to the users of the transmission system, like postage stamp, contract path, MW-mile, etc. [Shirmohammadi et al., 1994]. These methodologies are focused on determining wheeling costs, i.e., the cost incurred by specific electricity transactions using the network. Section 2.2.3.4 explained how, in the NEES network model implementation, the cost per unit of flow in the arcs associated to bulk electric energy transmission correspond to an estimation of the wheeling costs. Thus, the use of nodal price differences for calculation of profits is adequate in the context of assessing capacity expansion investments in the NEES.

Recalling from Chapter 4 that, in the optimal solution of the GMCFP, the nodal prices are given by the vector $-\boldsymbol{\pi}$, a nodal price $-\pi_k$ can be understood as the change in objective function (in this case the additional cost) of serving one extra unit of flow at node k. That is, in the context of the NEES network model, a nodal price at node j corresponds to the marginal cost of the energy served at that node. In a perfect

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[5] Financial Transmission Rights (FTRs) are financial instruments that entitle the holder to a stream of revenues (or charges) based on the day-ahead hourly energy price differences across the transmission path. [PJM, 2006]

competition context, the marginal cost is also equal to the price. Using these notions, we can develop nodal price-based metrics for the assessment of capacity expansion projects.

In Chapter 4, the reduced cost of an arc (*i*, *j*) was defined as a function of the nodal prices as follows:

$$c_{ij}^{\pi} = c_{ij} - \pi_i + \eta_{ij} \cdot \pi_j$$

According to the generalized flow optimality conditions theorem, a flow vector $\mathbf{e}^*$ is an optimal solution of the generalized minimum cost flow problem if it is feasible and for some vector π of node potentials, the following condition are met:

(a) If $0 < e_{ij}^* < e_{ij,\max}$, then $c_{ij}^{\pi} = 0$

(b) If $e_{ij}^* = 0$, then $c_{ij}^{\pi} \geq 0$

(c) If $e_{ij}^* = e_{ij,\max}$, then $c_{ij}^{\pi} \leq 0$

Looking more deeply into the reduced cost definition and the generalized flow optimality conditions theorem, we consider one unit of flow leaving node *i* to node *j*. Then $-\eta_{ij} \cdot \pi_j$ is the marginal cost (price) of the flow reaching node *j* (the potentials have negative values). Thus, the revenue made by the operator of the facility moving the flow from node *i* to node *j* is given by $-(\eta_{ij} \cdot \pi_j)$. Since $-\pi_i$ is the marginal cost (price) of the energy at node *i* and c_{ij} is the cost of moving one unit of flow from node *i* to node *j*, then $-c_{ij}^{\pi} = -(\pi_j \cdot \eta_{ij} - \pi_i) - c_{ij}$ is equal to the revenue per unit of flow less the cost per unit of flow, that is, the profit per unit of flow.

Thus, using the concept of profit, and based on the generalized flow optimality conditions theorem, we can say that for an optimal flow vector $\mathbf{e}^*$ the following conditions are met:

(a) If the flow in an arc is between its lower and upper limit, then the revenue per unit of flow is equal to the cost per unit of flow and therefore the profit per unit of flow for the respective arc is 0.

(b) If the flow in an arc is 0, then the revenue per unit of flow is equal or less than the cost per unit of flow and therefore the profit per unit of flow associated to the arc is equal or less than 0.

(c) If the flow in an arc reaches its upper limit (that is, the arc is congested), then the revenue per unit of flow is more than the cost per unit of flow and therefore the profit per unit of flow associated to the arc is more than 0.

In summary, investing in the most profitable arcs is also investing in the more congested arcs. Therefore, using reduced costs as a metric for the assessment of capacity expansion projects not only provide investors signals of the locations where a potential investment would be more profitable, but it can also inform central planners where capacity expansions should take place in order to reduce congestion.

In microeconomics theory, long-run competitive equilibrium conditions in a market of price-takers with free entry and exit imply that positive profits draw entry of new firms (capacity increase), increasing industry supply and lowering prices until the profits are down to zero, that is, to a point where there is no longer congestion in the respective arc. Also in the long-run, negative profits cause exit of existing firms (capacity decrease), raising prices until profits are up to zero. If for any given arc in the NEES network model there is no congestion, then in the average the profit for the facilities being represented by that arc is zero, that is, there is no entry or exit of firms (no capacity expansion or reduction). Therefore, an important consequence of assessing congestion is also to inform the decision making related to capacity expansion investments from the investor point of view.

The cost of an arc represents the weighted average of the costs of the facilities aggregated in that arc. Thus, not all the facilities will have the same profit. Those with a cost over the average cost will have a profit per unit of flow below the average, and those facilities with a cost below the average cost will have a profit per unit of flow over the average. Hence, the profit per unit of flow associated with any given facility can be calculated by replacing the average cost per unit of flow of the corresponding arc by their own cost per unit of flow.

6.4 Vulnerability assessment

Vulnerability is understood as the susceptibility to degradation or damage from adverse factors or influences. Considering that the NEES intended function is to deliver electric energy to costumers within accepted standards and in the amount desired [Ringlee et al., 1993], the vulnerability assessment proposed in this section estimates how susceptible is the system to reach a condition where the demand exceeds the transportation network ability to supply the demand. To achieve this goal, the GMFP is solved in order to obtain the maximum flow that the network is able to deliver from the source node *s* to the sink node *t*, that is, the system's capacity w_0, which is calculated as the sum of the capacities of the arcs belonging to the minimal cut-set of minimum capacity (MC_0).

Figure 6.2 illustrates the difference between the capacity-based metric proposed in this section and the nodal price-based metrics proposed in Sections 6.2 and 6.3. Note that the system capacity constitutes a physical upper bound for the demand that the network is able to satisfy.

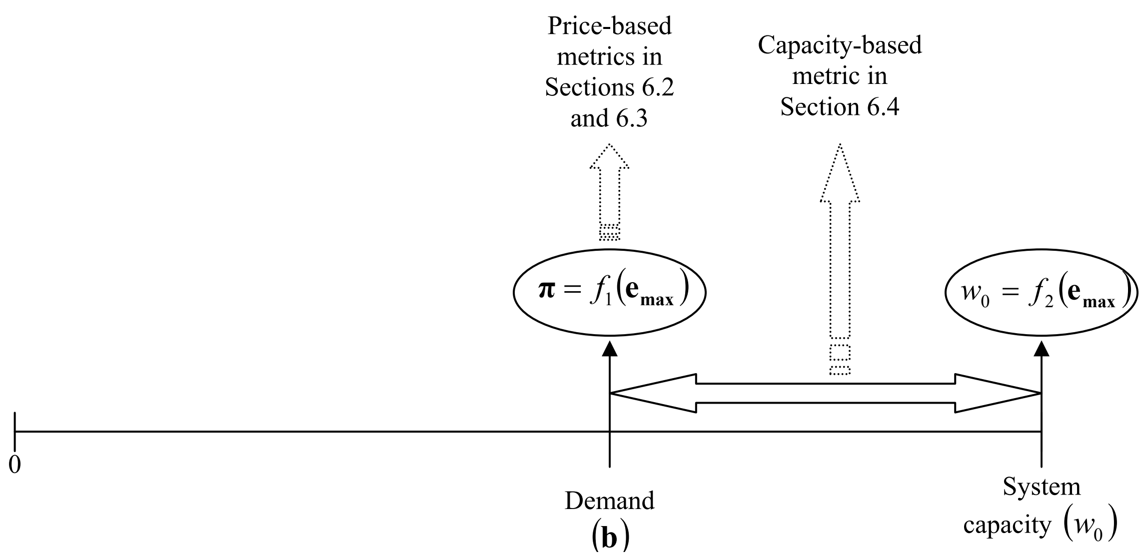

Figure 6.2. Price-based and capacity-based metrics

The nodal price vector $\boldsymbol{\pi}$ is a function of the graph *G*, the vector of costs **c**, the vector of efficiencies $\boldsymbol{\eta}$, the vector of capacities $\mathbf{e_{max}}$, the vector of demands **b,** the source node *s* and the sink node *t*. That is, $\boldsymbol{\pi} = f_1(G, \mathbf{e_{max}}, \mathbf{c}, \boldsymbol{\eta}, \mathbf{b}, s, t)$. The system capacity w_0 is a function of the graph *G*, the vector of capacities $\mathbf{e_{max}}$, the source node *s* and the sink node *t*. That is, $w_0 = f_2(G, \mathbf{e_{max}}, s, t)$. For simplicity, only the functionality in terms of $\mathbf{e_{max}}$ is depicted in Figure 6.2.

On the one hand, the metrics described in Sections 6.2 and 6.3 deal with changes to the system's operating point (specified by the vector of nodal prices $\boldsymbol{\pi}$) as a consequence of changes in the vector of arc capacities $\mathbf{e_{max}}$. In particular, the approach introduced in Section 6.2 for evaluating the impact of a disruption assesses the change in nodal prices $\boldsymbol{\pi}$ due to a smaller[6] vector of arc capacities $\mathbf{e_{max}}$, while the approach introduced in Section 6.3 for assessing capacity expansion projects evaluates the change in nodal prices $\boldsymbol{\pi}$ due to a larger vector of arc capacities $\mathbf{e_{max}}$.

On the other hand, the interest in this section is to evaluate how close is the system to reach a condition where the demand exceeds the transportation network ability to supply the demand. This is achieved by calculating the difference between the system capacity (w_0) and the total demand $\left(\sum b_i\right)$.

As the demand gets closer to the system capacity, the system becomes more congested and the nodal prices increase. The demand will become closer to the system capacity if there is a demand increase or if there is a capacity reduction in one or more major facilities, for example, as a result of a catastrophic event. If at some point the system capacity is less than the demand, there the network will be incapable of satisfying all the demand.

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[6] We say that a vector $\mathbf{e^*_{max}}$ is smaller than a vector $\mathbf{e_{max}}$ if $e^*_{\max,ij} \le e_{\max,ij}$ for all pairs (*i*, *j*) and $e^*_{\max,ij} < e_{\max,ij}$ for at least one pair (*i*, *j*). We say that a vector $\mathbf{e^*_{max}}$ is larger than a vector $\mathbf{e_{max}}$ if $e^*_{\max,ij} \ge e_{\max,ij}$ for all pairs (*i*, *j*) and $e^*_{\max,ij} > e_{\max,ij}$ for at least one pair (*i*, *j*).

In 1956, Ford and Fulkerson proved in their seminal paper the max-flow min-cut theorem [Ford & Fulkerson, 1956]. The theorem states that the maximum possible value of the flow from the source s to the sink t is equal to the minimum capacity among all cut-sets. The capacity for a minimal cut-set can be calculated as the sum of the capacities of the arcs in the cut-set. If we assume all the capacities in the arcs to be positive, then we realize that the cut-sets that are not minimal cut-sets are redundant, so we can re-state the theorem as follows: the maximum value of the flow from the source s to the sink t is equal to the minimum capacity among all minimal cut-sets.

From the Ford & Fulkerson theorem we can realize that the arcs belonging to the minimal cut-set with the minimum capacity are critical, since this minimal cut-set is the bottleneck in the transportation network. Capacity expansions in the facilities located in this minimal cut-set would make the system more robust and reliable. Thus, identification of vulnerabilities in the context of the NEES network model corresponds to discover the arc or set of arcs whose disruption would have major impact in terms of the ability of the transportation network to satisfy the demand.

Even though the minimal cut-set with the minimum capacity is the one with the smaller gap between its capacity and the demand, there may be other minimal cut-sets whose capacity is just a little higher that may also be relevant and interesting to analyze. Thus, another further step can be to enumerate all the near-minimum capacity minimal cut-sets, that is, minimal cut-sets whose capacity is within a factor of $1+\varepsilon$ of the capacity of the minimal cut-set.

The goal of the enumeration of all near-minimum capacity minimal cut-sets technique proposed in this section is to detect points where the energy system may be vulnerable and in this way serve as an indicator to the decision makers of specific infrastructures that may be critical in the energy system operation. In terms of data requirements, to be implemented the algorithm for enumeration of all near-minimum capacity minimal cut-sets only needs the structure of the network and the capacities of the arcs.

Enumeration of all near-minimum minimal cut-sets is a technique developed to solve the problem of network interdiction. Network interdiction is a problem common to military applications, and consists of attacking an adversary's network with the objective of minimize the network functionality using limited resources. The same idea can be used with the purpose of identifying where the system is more vulnerable in order to offer extra protection to the most critical energy infrastructure.

Additionally, if we know which of the minimal cut-sets are more important in terms of system vulnerability, and we know the probability distributions of the capacities of the arcs belonging to those minimal cut-sets, we could provide focus only on the analysis of the most likely scenarios. Since the arcs in the network model of the NEES represent actual routes (either individual or aggregated transportation facilities) of the US energy system, an assessment of this nature will be useful to establish where the system needs to be strengthened, where to take special precautions to protect the system, or to elaborate contingency plans.

The all near-minimum capacity minimal cut-sets enumeration algorithm used to assess the vulnerability of the NEES is based on the algorithm introduced in [Balcioglu and Wood, 2003]. The algorithm introduced there is not designed for generalized networks like the NEES network model, so changes were introduced so that it could be used in this work. These changes consist in scaling the capacities of the arcs counter-flow-wise using the average efficiency value of the gas-fired generators for the natural gas-subsystem and using the average efficiency value of the coal-fired generators for the coal subsystem. With these changes, the network is transformed into a standard network (not generalized) and all the capacities will be on MWh-equivalent units. The scaling process is based in the following assumptions and considerations:

- The efficiencies of different coal-fired generators are similar to each other.
- The efficiencies of different gas-fired generators are similar to each other.
- The natural gas subsystem is only linked to the coal subsystem through the electric subsystem.

- Energy flows from the coal and natural gas subsystems to the electric subsystem, and not vice versa.
- The efficiencies of the arcs within each subsystem are small enough to be neglected.

```
begin
    e_max ← ScaleGasSubsystem(G, e_max)
    e_max ← ScaleCoalSubsystem(G, e_max)
    [w_0, MC_0] ← MaxFlow(G, s, t, e_max)
    w_ε ← (1 + ε)·w_0
    E+ ← φ        E- ← φ
    Enumerate(G, s, t, e_max, E+, E-, w_ε)
end

Procedure Enumerate(G, s, t, e_max, E+, E-, w_ε)
begin
    e_max' ← e_max
    G' ← G
    for each arc (u,v) ∈ E-        e_uv,max' ← ∞
    for each arc (u,v) ∈ E+ begin
        Add dummy arc (s,u) to G' and let e_su,max' ← ∞
        Add dummy arc (v,t) to G' and let e_vt,max' ← ∞
    end
    [w', MC'] ← MaxFlow(G', s, t, e_max')
    if w' > w_ε return
    if MC' is minimal in G' print (MC')
    for each arc (u,v) ∈ MC' − E+ begin
        E- ← E- ∪ {(u,v)}
        Enumerate(G, s, t, e_max, E+, E-, w_ε)
        E- ← E- − {(u,v)}
        E+ ← E+ ∪ {(u,v)}
    end
    return
end
```

The algorithm begins by calling the procedures *ScaleGasSubsystem* and *ScaleCoalSubsystem*. *ScaleGasSubsystem* scales the capacities of the arcs in the coal subsystem counter-flow-wise using the average efficiency value of the coal-fired generators. *ScaleCoalSubsystem* scales the capacities of the arcs in the natural gas-subsystem counter-flow-wise using the average efficiency value of the gas-fired generators. The units of all the capacities of the arcs in the network will now be in MWh, and its efficiencies can be approximated to 1 (considering the previously stated assumptions).

From then, the algorithm behaves exactly as the algorithm *B* introduced in [Balcioglu & Wood, 2003]. This algorithm finds (in the modified network) the minimal cut-set of minimum capacity MC_0 and its capacity w_0. Then, the algorithm calls the procedure *Enumerate* which attempts to find a new minimal cut-set by processing the arcs of the initial cut such that the arcs are forced into or out of any new near-minimum capacity minimal cut-set. The procedure calls itself recursively for every arc of the locally minimum cut that has not already been forced into that cut at higher level in the enumeration. The procedure backtracks when it determines that no acceptable cuts remain below a given node.

7 Numerical results

This chapter presents numerical simulation results from the NEES network model. Section 7.1, *Model validation*, compares actual with simulated values of energy flows and prices, in order to validate the capabilities of the model and to check the accuracy and correctness of the 2005 data used for the node and arc parameters. Section 7.2, *Evaluating the impact of hurricanes Katrina and Rita*, study the impact of disruptions on the NEES, using data obtained on the hurricanes Katrina and Rita effects on the parameters of the NEES. Section 7.3, *Assessment of capacity expansion investments*, identifies profitable locations for adding new capacity by using the metrics described in Section 6.3, and it also illustrates the use of the metric for a hypothetical capacity expansion project. Finally, Section 7.4, *Assessment of vulnerabilities in the NEES*, presents the results of the algorithm introduced in Section 6.4 to assess the vulnerability of the NEES in terms of available transportation capacity.

7.1 Model validation

The final bulk energy movements in the real energy system are determined by multiple decision makers with different levels of control over the system variables trying to maximize their own objective function (usually profits). On the other hand, simulation results for the NEES network model provide a set of energy flows such that the total cost for the entire system is minimized, that is, it considers a centralized decision maker. Even though there is a difference between how decisions are made in the real system and how they are made in the NEES network model, the final objective of the NEES network model is not necessarily to replicate reality, but to provide benchmark results associated with optimal decision-making and to offer analysis tools for identifying system weaknesses and associated investment alternative, as described in previous chapters. Nevertheless, under certain restricted simulation conditions, simulated decision variables should approximate to actual ones. The comparison between them can be used to validate model assumptions and the values of the network parameters.

A preliminary validation of an earlier version of the NEES network model (using 2002 data) was carried out in [Quelhas, 2006], where the reference case was designed with the actual configuration of generation and loads reported on a monthly basis for the year 2002. That is, coal-fired net generation and gas-fired net generation for each region and for each time step were fixed, together with the total emissions for 2002. This approach validated the model's ability to replicate fuel production and transportation the generators. This validation effort reported aggregated simulation results, with annual total flows and annual average prices. Even though overall those results constituted a good match for the actual system operation, no figures were presented to compare actual data with simulated results in time. Actual monthly data indicates that 2002 was a relatively normal year, with no sharp short-term increases in prices nor major perturbations or large-scale contingencies worthy of specific analysis. In summary, the validation approach presented in [Quelhas, 2006] and [Quelhas et al., 2007] seems to be appropriate in that context.

On the other hand, hurricanes Katrina and Rita, despite their dramatic cost in terms of human lives, made of 2005 a very interesting year for testing the performance in time of the model and to identify underlying system interdependencies. In the validation for the 2005 NEES network model presented in this section, instead of fixing all generation as in the 2002 case, only the loads and the total coal-fired net generation per month and per NERC region were fixed. Therefore optimization was performed on the coal, natural gas, and electricity flows. This reference case used for validation is less restrictive than the case used for the validation done using the 2002 implementation of the network model, as it allows more freedom for the variables to change, especially the variables in the natural gas subsystem which were directly affected by the hurricanes in 2005. The purpose of this validation scheme is to test the ability of the model to reflect the effects of hurricanes Katrina and Rita in the U.S. energy system, and to capture how these effects (in terms of energy prices) propagated across time, space, and subsystems characterizing bulk energy transportation. Results of the simulation are compared to the corresponding historical values in Tables 7.1, 7.2, and 7.3

Validation of the model is to some extent limited by the availability of publicly available data. Most of the publicly available data is presented in a much aggregated form in order to not disclose individual company data.

The resulting total coal production and total natural gas production and imports are presented in Table 7.1, where they are compared with the actual values obtained from the EIA website. It can be observed that the U.S. national natural gas production is underestimated by the model, while the total natural gas imports from Canada is overestimated. However, the total production plus imports is very close to the actual value. This means the model indicates that for 2005 it would have been cheaper to import natural gas from Canada than produce it locally, probably as a result of the high local production prices due to hurricanes Katrina and Rita in 2005. The difference in coal production, while small, can be attributed to changes in coal stocks by producers and power plants, which were not considered in the calculations because of the lack of publicly available data.

Table 7.1. Validation results: Total coal and natural gas production and imports

Result	**Model**	**Actual**	**Difference**
NG total production [Bcf]	17,200	18,244[7]	-5.52 %
NG imports from Canada [Bcf]	4,280	3,700	+15.56%
NG production plus imports [Bcf]	21,480	21,944	-2.11%
Coal production [billion short ton]	1.08	1.128	-4.3%

The total natural gas and coal consumption, and the total natural gas- and coal-fired generation are presented in Table 7.2. Since the demands of natural gas by non-

[7] Dry production

power users at each natural gas transshipment node and the coal-fired net generation per month and per region are fixed in this reference case, their values are exactly the same as the actual value. Since the use of different load levels within a monthly period is restricted to the NY-ISO and ISO-NE electric transshipment nodes (because of the lack of additional data, as indicated in Section 3.4), in general the optimization algorithm assign flows only to the more cheap and efficient gas-fired generation and not to the more expensive and inefficient, which in practice is only used for high electric load levels. Thus, it is reasonable for the CPLEX solution to underestimate the natural gas consumption, which is about 6% lower than the actual consumption.

Table 7.2. Validation results: Total coal and natural gas consumption and generation

Result	**Model**	**Actual**	**Difference**
NG consumed by electric sector [Bcf]	5,936	5,869	1.15%
NG consumed for uses other than power [Bcf]	14,500	14,500	0%
Gas-fired net generation [MWh]	712.63	757.97	-5.98%
Coal consumed by electric sector [billion short ton]	1.00	1.038	-3.66 %
Coal-fired net generation [MWh]	1,917.45	1,917.45	0%

The average costs of natural gas and coal to electric utilities and the average electric energy price for 2005 are presented in Table 7.3. The differences between simulated and actual values, although relatively small, might be attributable to the lack of good quality publicly available data concerning energy transportation costs.

Table 7.3. Validation results: Average costs of fuel for electric generation and electric energy price

Result	**Model**	**Actual**	**Difference**
Cost of NG for electric power [$/Mcf]	9.02	8.49	6.2%
Cost of coal for electric power [$/short ton]	29.61	31.22	-5.2%
Electric energy price [$/MWh]	78.5	81.4	-3.6%

Since no major disruptive events or changes in energy movements or prices happened in 2002 (that is, very flat prices and flows through the year), in the preliminary validation effort presented in [Quelhas, 2006] no comparisons between behavior in time of simulated and actual values were deemed necessary. Neither was it deemed necessary at the time to carry out any comparisons between dual variables obtained from simulation (nodal prices) and actual energy prices, nor comparisons of simulated and actual values at different geographical locations. Thus, only comparisons for a very limited number of aggregated variables were performed. On the other hand, the impact of hurricanes Katrina and Rita on natural gas production and transportation capacities and on energy prices during 2005 is easily observable, making 2005 an ideal case for testing some of the most interesting system capabilities, such as the use of different time steps for each subsystem.

In order to validate the dynamic performance of the model, and to measure the model's ability to capture the effects in prices of specific changes on the network parameters, comparisons between nodal prices obtained in the model and actual energy prices were performed. Figure 7.1 illustrates the average nodal price of natural gas at the natural gas transshipment nodes. This average nodal price is obtained by calculating, for each month, the weighted average of the nodal prices at each natural gas transshipment node, as obtained by CPLEX. The natural gas cost for electric power corresponds to the price at which gas-fired power plants buy natural gas. The simulated values follow closely the actual ones, and the effect on the natural gas price following Katrina (in August) is clearly reflected in the simulated curve.

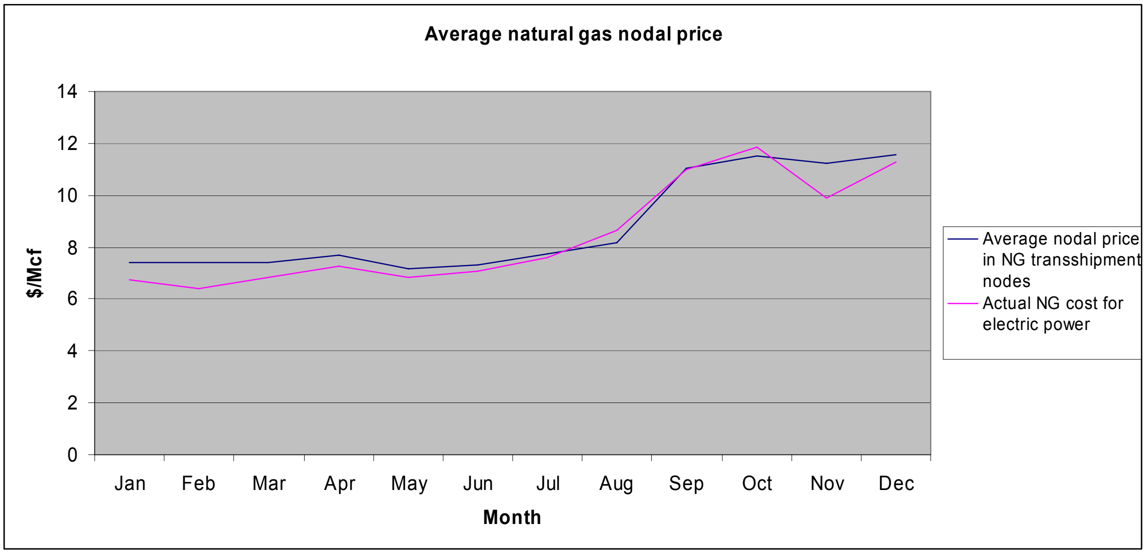

Figure 7.1. Average natural gas nodal price

Figures 7.2 and 7.3 illustrate simulated evolution of nodal prices in the NY-ISO electric transshipment node. While Figure 7.2 results correspond to a simulation carried out using a single load level for NY-ISO and ISO-NE, Figure 7.3 results correspond to a simulation using 3 load levels for each node. These simulated values are compared to the real-time LMP values recorded in the NY-ISO hub during 2005.

It is observed that nodal prices as obtained by the NEES network model and real-time LMPs are not the same, since LMPs also depend on other factors that are out of the scope of the current research, like market uncertainty and/or local congestion within the region. However, the comparison of their patterns can be useful to check if the effects of higher natural gas prices due to Katrina permeate to other subsystems, and it also sheds some light on the question of whether the NEES network model is able to capture interdependencies between different energy subsystems.

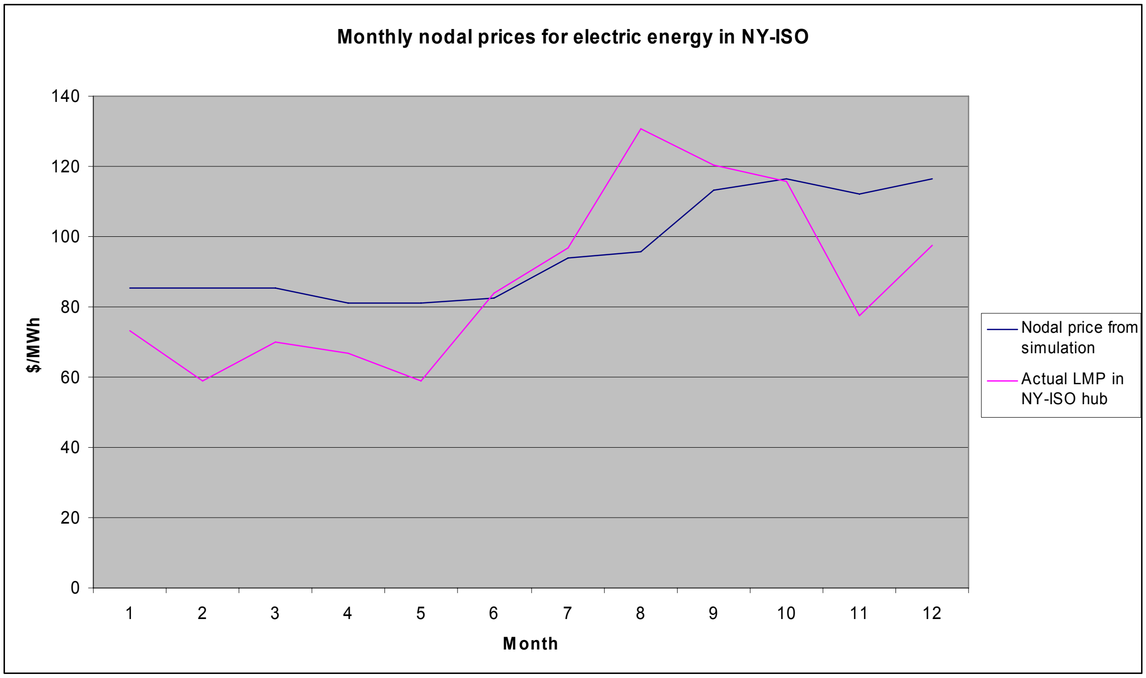

Figure 7.2. Actual and simulated monthly nodal prices in NY-ISO without load levels

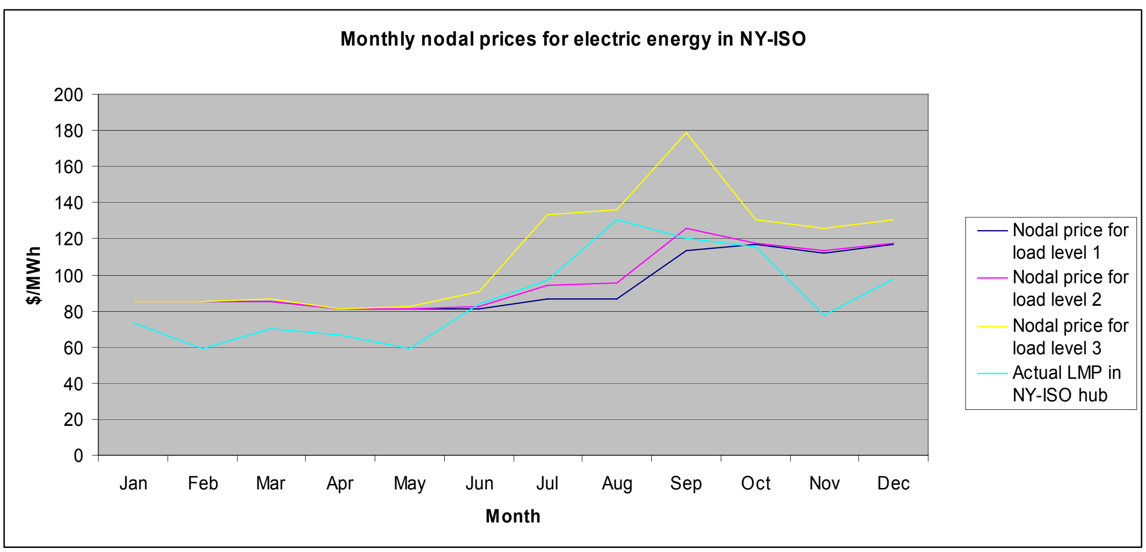

Figure 7.3. Actual and simulated monthly nodal prices in NY-ISO with load levels

While both simulations show the capability at some level of the NEES network model to capture the effects on electric prices of a disruption, comparison between

Figures 7.2 and 7.3 clearly indicates that the use of more than a single load level to represent electric load can greatly improve the simulation. This assertion will be further corroborated when the simulation results of Figures 7.4, 7.5, and 7.6 are described.

As explained in Chapter 3, gas-fired generation is more expensive than coal-fired generation, so natural gas is typically used when the electric demand is over a certain load threshold such that all coal-fired units are operating at their maximum capacity. For this reason, many natural gas power plants do not operate continuously, but only on periods of high demand. Many small capacity natural gas generating units are referred to as “peakers”, meaning that they only operate at peak or close to peak electric load. If the model is not able to represent periods when peak demand occurs, then in the simulation results some of the more expensive generating units (the ‘peaker’ units) will never be used, which is unrealistic and may lead to underestimating electricity prices and natural gas use for generation. The significant underestimation of natural gas use for electric generation reported in [Quelhas, 2006], where a single load level is used, is mainly an indication of this fact.

Figure 7.4 and Figure 7.5 show the use of natural gas generation capacity in ISO-NE and NY-ISO for the 3 different load levels. It is clear that the differences in use of natural gas generation capacity at different load levels are significant. The consequences of not modeling variation of load level are inaccuracy on the calculation of electricity prices, congestion levels, and fossil fuel use.

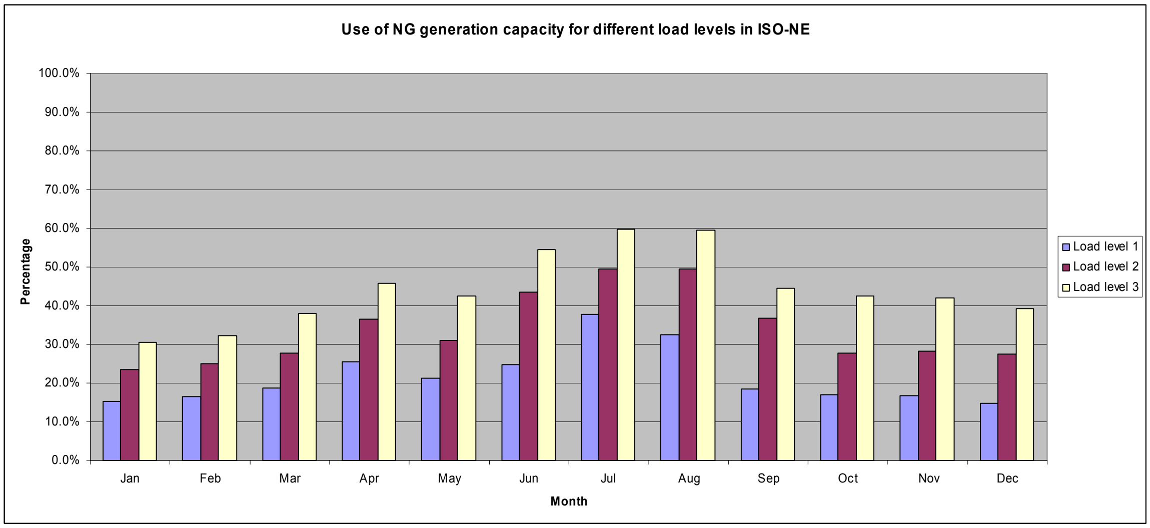

Figure 7.4. Use of NG generation capacity in ISO-NE with load levels

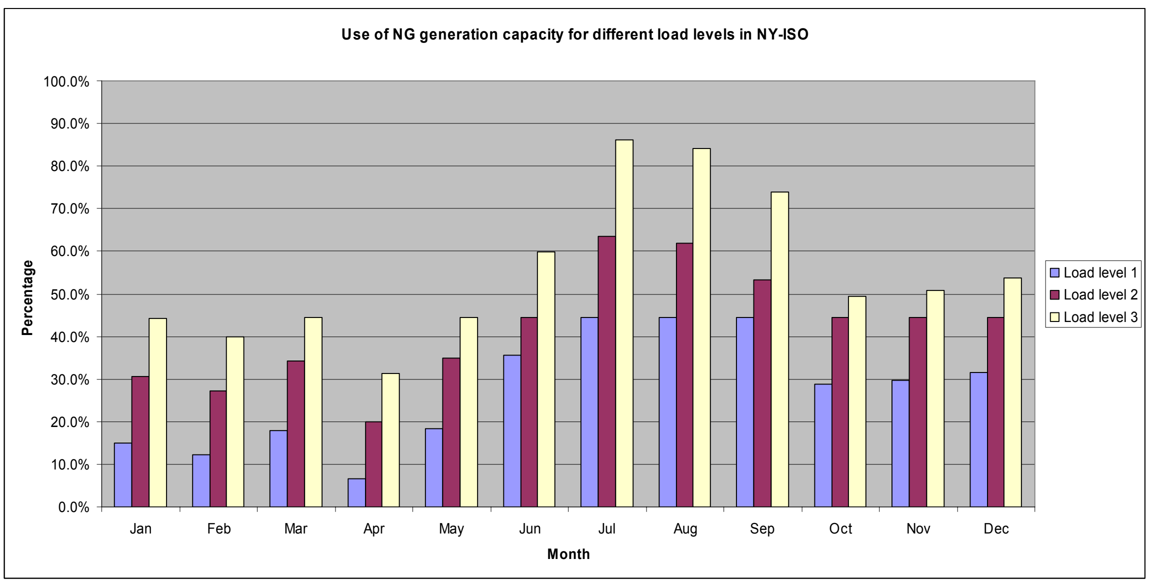

Figure 7.5. Use of NG generation capacity in NY-ISO with load levels

The effects of the use of 3 different load levels for representation of the electric load are further illustrated by Figure 7.6. As shown in this figure, when using a single load level, there is only congestion in the transmission line between NY in July and August 2005. Congestion (and the consequent higher prices) is not observed the rest of the time. On the other hand, using 3 different levels of load, we get a very different insight into the actual use of different facilities and the existence of congestion, which consequently also leads to a better estimation of the electric energy prices, as shown in Figures 7.4 and 7.5.

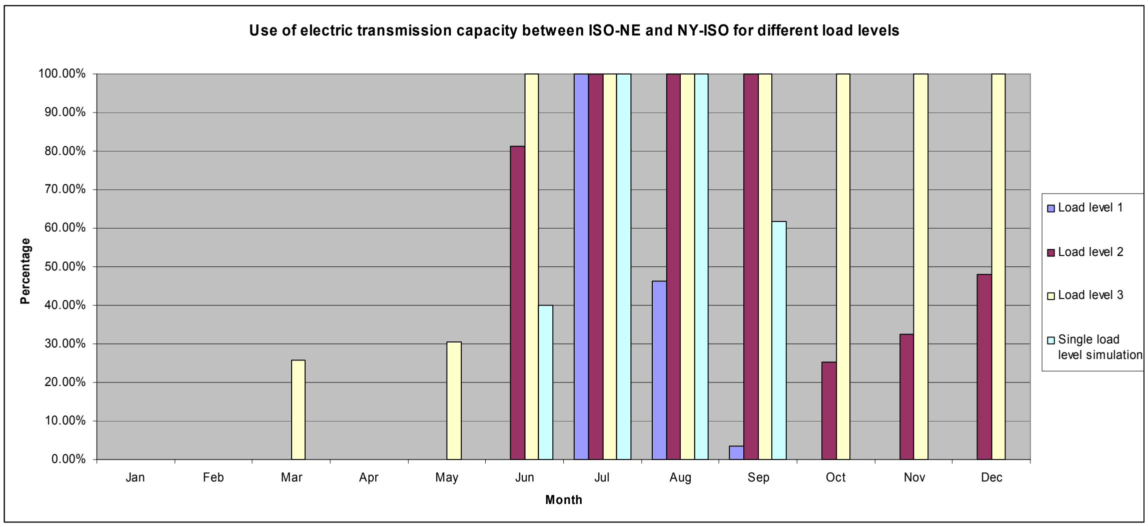

Figure 7.6. Use of electric transmission capacity between ISO-NE and NY-ISO with load levels

In conclusion, from the comparison of simulated and actual data, we can say that, although some differences should be expected, the model follows the trends observed in prices and flows and is capable to reproduce effects of hurricanes Katrina and Rita on energy prices. The technique of disaggregating the electric demand by load levels proved to be adequate greatly extended the analytical capabilities of the NEES network model. Further disaggregation of other electric transshipment nodes using load levels, as more data becomes available, might be necessary to improve the accuracy of the model, especially in the electric subsystem.

7.2 Evaluating the impact of hurricanes Katrina and Rita

In order to evaluate the impact of hurricanes Katrina and Rita, a comparison of nodal prices with and without the hurricanes was performed. The case with the hurricanes is the same as the reference case used in Section 7.1. The case without the hurricanes was developed by leaving the capacities of the arcs at their normal values and adjusting natural gas production costs to values forecasted by EIA for the corresponding months.

The case without the hurricanes was developed starting from the case with the hurricanes. Considering an elastic demand, the lower costs of natural gas and electric energy without the hurricanes would have motivated a higher demand. Thus, the demand at the electric and natural gas transshipment nodes was adjusted as described in Chapter 3, and the results of the simulation are presented in Table 7.4

Table 7.4. Total system cost with and without the hurricanes

Case		**Total system cost** [billion $]
With Katrina		174.08
Without Katrina	Demand with no elasticity adjustment	161.00
	Demand with elasticity adjustment (1 iteration)	163.87
	Demand with elasticity adjustment (2 iterations)	163.63

According to the results in Table 7.4, the cost of Katrina in terms of additional energy costs is about $10.5 billion from September to December 2005. Once data for 2006 becomes available (by the end of 2007), it will certainly be possible to extend the simulation to the point where facilities are all completely back in service, where it should be expected that nodal price curves would come back down very close to the case without Katrina. This would provide an indication of the total additional energy cost in the NEES as a consequence of the 2005 hurricanes.

The change in the total system cost as a result of including elasticity on the model is rather small (less than 2%). However, the difference in nodal prices as a result of including elasticity in the model was larger. The differences of the case with no elasticity adjustment and the case with elasticity adjustment (1 iteration) were up to 7.8%, and the differences in nodal prices between the cases with 1 and 2 iterations of elasticity adjustment were less than 2%. The iterative process converged fast, and differences in nodal prices when executing more iterations were less than 0.5%, and were considered negligible.

Figure 7.7 shows the evolution of nodal prices at the 6 natural gas transshipment nodes, with and without Katrina, by illustrating how the effects of Katrina and Rita propagated geographically and in time. Although the different curves look similar to each other, there are some noteworthy differences, which are made clearer in Figure 7.8.

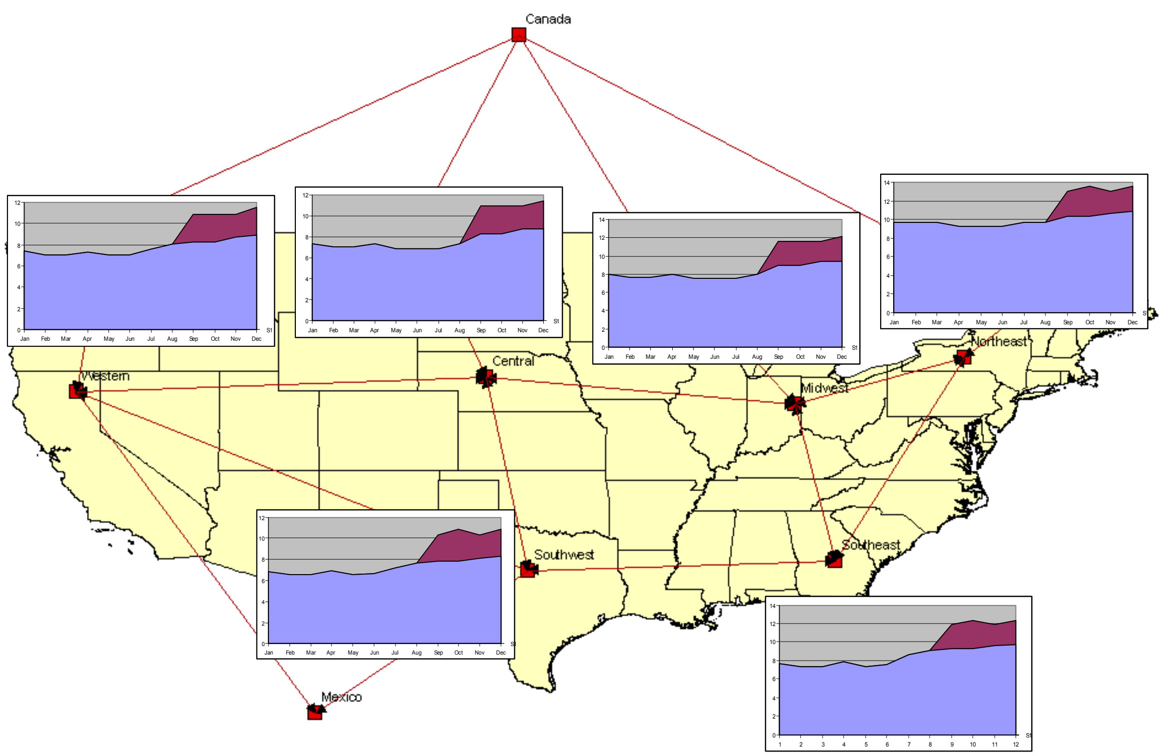

Figure 7.7. Effect of hurricanes Katrina and Rita in natural gas nodal prices

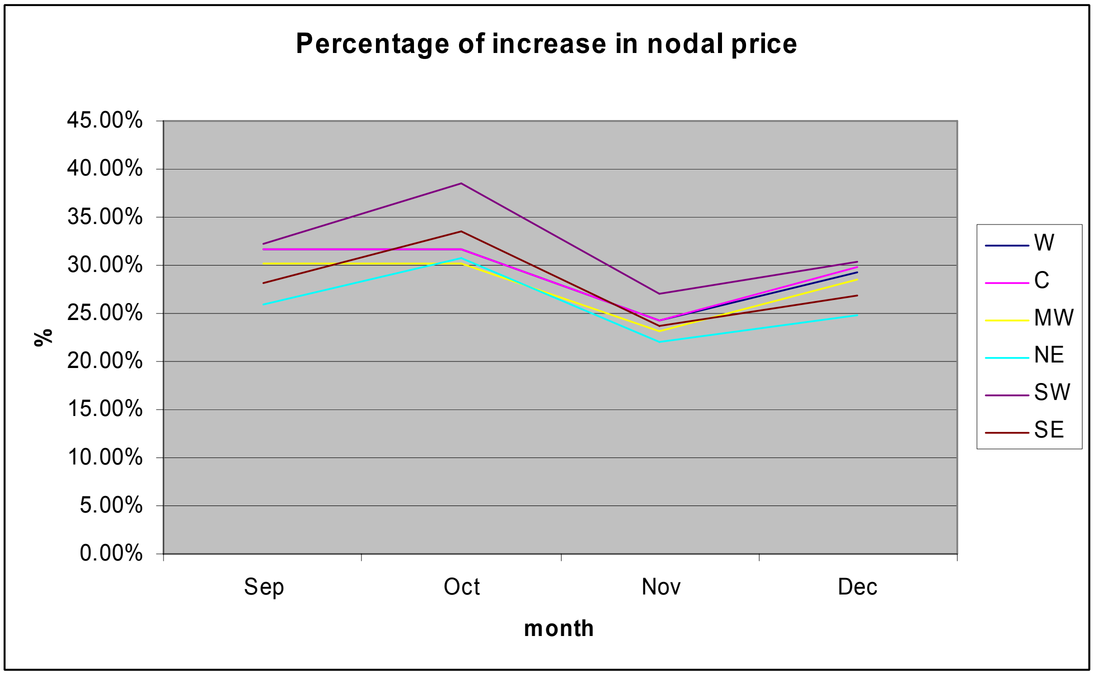

Figure 7.8. Percentage of increase in natural gas nodal price with the hurricanes

It is clear from Figure 7.8 that the node with the larger increase was the Southwest (representing the gulf region and the southwest US) natural gas transshipment node, which is reasonable considering that it is the node directly affected by the hurricanes. While still affected in terms of relative increase in nodal prices, the less affected nodes were the Midwest and Northeast nodes, which incidentally are the only natural gas transshipment nodes not directly connected by an arc to the Southwest node. This suggests, as it is reasonable to suspect, that the effects of a disruption are more severe in the nodes that are closer to it.

7.3 Assessment of capacity expansion investments

7.3.1 General assessment

In Chapter 6 it was discussed how the reduced costs provided by the CPLEX solution to the GMCFP correspond to the negative of the profit per unit of flow (hereafter called per-unit profit) of the facilities related to a particular arc of the NEES network model. It was also discussed how these values are related to congestion, and the way they can be used to assess capacity expansion investments.

Figure 7.9 illustrates the average per-unit profits in the arcs representing transportation in the natural gas subsystem, while Figure 7.10 shows the average per-unit profits in the arcs representing transportation in the electric subsystem. Transportation corridors with a higher per-unit profit are the more attractive for investments. Arcs in blue represent congested arcs which, as explained in Chapter 6, are the most attractive for investments. Arcs in red represent arcs with no congestion, and where investment is not attractive.

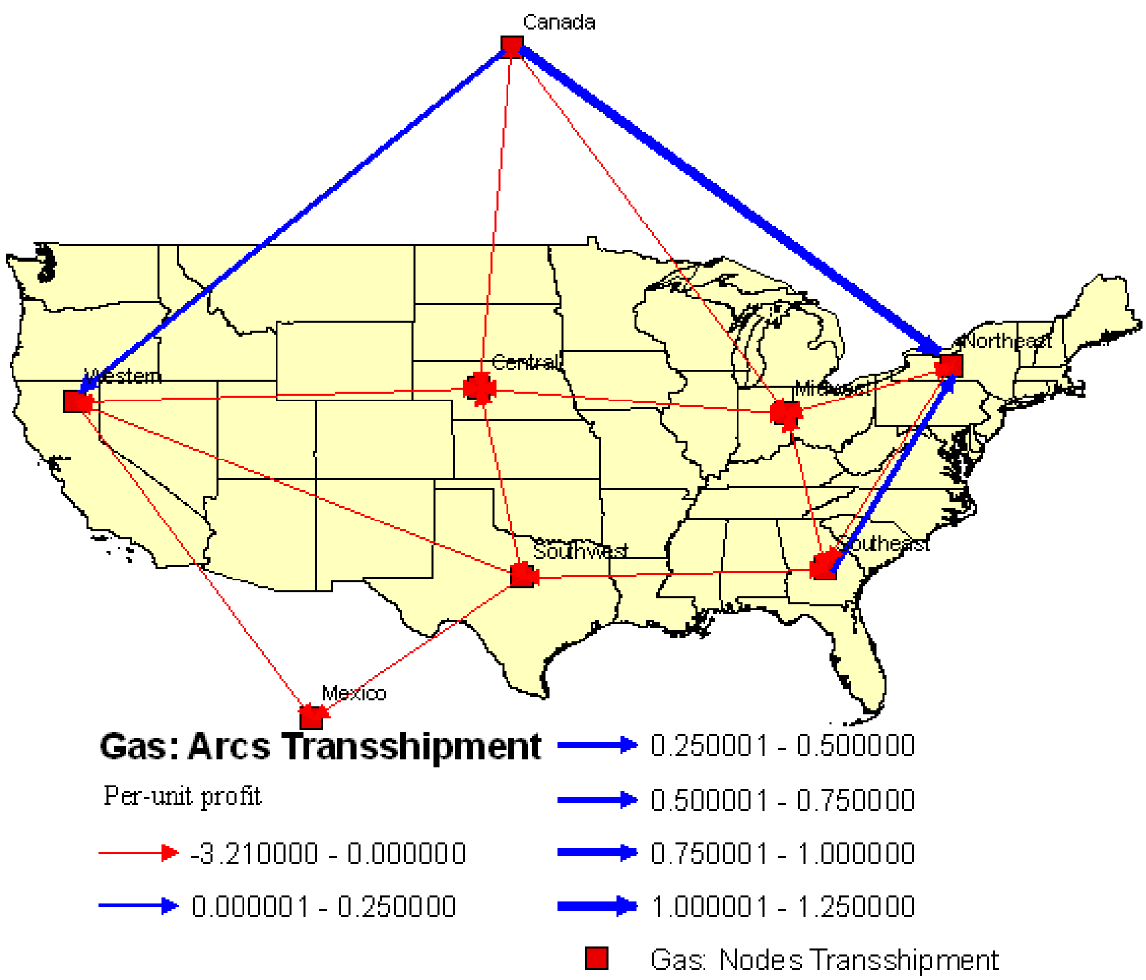

Figure 7.9. Profits per unit of flow in the natural gas subsystem

Most of the congestion in the natural gas subsystem concentrates in the arcs going to the Northeast transshipment node. This observation is confirmed by the fact that the price of natural gas in the Northeast is the highest in the country.

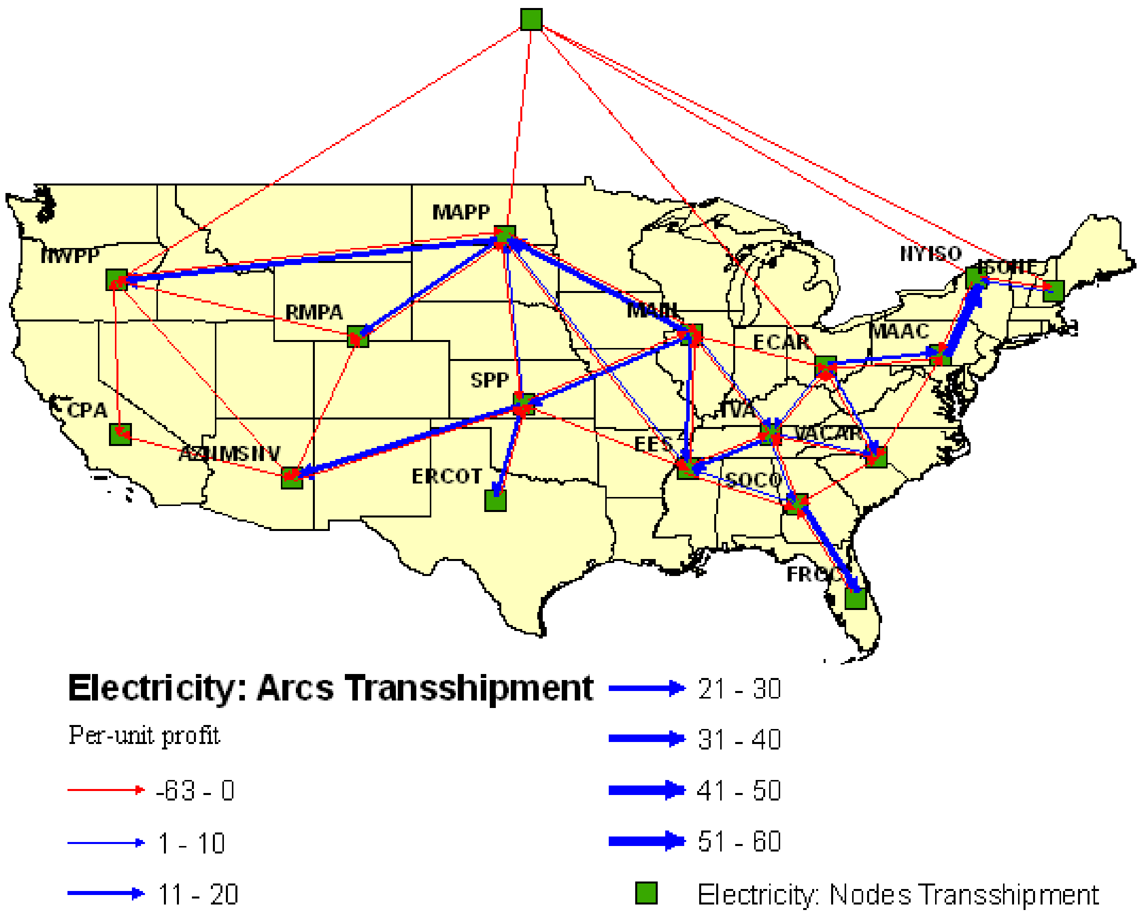

Figure 7.10. Profits per unit of flow in the electric subsystem.

To calculate the metric the existence of an arc connecting any pair of nodes is not necessary, since they can be assumed as being connected by an arc with capacity equal to 0. The profit per unit of flow for any pair of nodes i and j can be simply calculated using their respective nodal prices as $\eta_{ij} \cdot p_{j,t} - p_{i,t} - c_{ij}$. With the purpose to illustrate how the metric can be used to inform capacity expansion decisions by helping prioritize the most profitable transmission corridors, Figure 7.11 presents the profit per unit of flow for any pair of electric transshipment nodes. The results presented in Figure 7.11 are intended for illustrative purposes only, since it is assumed that the efficiency and the cost per unit of flow is the same for any pair of nodes, which in an overly simplifying assumption made necessary for the lack of additional data.

CAL	AZNM	RMPA	MAPP	SPP	ERCT	MAIN	ECAR	ENTG	TVA	VACA	SO	FRCC	MAAC	NYISO	ISONE	
-	-	1.2	21.6	25.9	11.5	49.9	51.0	25.8	45.2	35.0	33.9	-	36.3	15.0	6.3	**NWPP**
	-	3.8	24.2	28.5	14.1	52.5	53.6	28.4	47.8	37.6	36.5	-	38.9	12.3	3.6	**CAL**
		0.3	20.7	24.9	10.6	48.9	50.1	24.9	44.3	34.0	32.9	-	35.3	15.9	7.2	**AZNM**
			16.9	21.2	6.8	45.1	46.3	21.1	40.5	30.3	29.2	0.6	31.6	19.8	11.1	**RMPA**
				1.2	6.8	25.2	26.3	1.1	20.5	10.3	9.2	21.0	11.6	40.2	31.5	**MAPP**
					11.1	21.0	22.2	-	16.3	6.1	5.0	25.2	7.4	44.4	35.7	**SPP**
						35.1	36.2	11.0	30.4	20.2	19.1	10.9	21.5	30.1	21.4	**ERCT**
							-	21.0	2.1	12.1	13.2	49.2	10.8	68.4	59.7	**MAIN**
								22.2	3.2	13.3	14.3	50.4	12.0	69.6	60.9	**ECAR**
									16.4	6.2	5.1	25.2	7.5	44.4	35.7	**ENTG**
										7.4	8.5	44.6	6.1	63.8	55.0	**TVA**
											-	34.3	-	53.5	44.8	**VACA**
												33.3	-	52.4	43.7	**SO**
													35.7	15.6	6.9	**FRCC**
														54.8	46.1	**MAAC**
															4.9	**NYISO**

x	x>56
x	42<x<56
x	28<x<42
x	14<x<28
x	0<x<14
-	x<0

Figure 7.11. Profit per unit of flow in the electric subsystem for all the possible arcs

The most congested of the existing arcs in the electric transmission system is the arc going from MAAC to NY-ISO, with an average per-unit profit of 54.8 $/MWh. As a consequence of this, it is the most profitable of the existing arcs to invest in capacity expansion. The high per-unit profit in this arc is a clear indication of congestion preventing cheaper generation in MAAC to be exported to NYISO region.

According to the a DOE-funded project called "Transmission Bottleneck Project" conducted in 2003 [CERTS, 2003], congestion costs in NY-ISO over a three year period averaged in excess of $900 million per year, and NY-ISO was the number one priority for addressing bottlenecks, which supports the results presented in Figure 7.10. Furthermore, one of the ideas strongly recommended in [CERTS, 2003] to reduce congestion in NY-ISO was to expand the transmission capacity between PJM (MAAC) and NY-ISO, which further confirm the validity of the results.

Another view of per-unit profits associated with the arc between MAAC and NY-ISO are shown in Figure 7.12, where per-unit profits are presented for different load levels. The high values that profits reach during high congestion time periods are observable. For load level 3 (higher load level, 10% of the time), in September the per-unit profit reaches almost 3 times the average profit of 56 $/MWh.

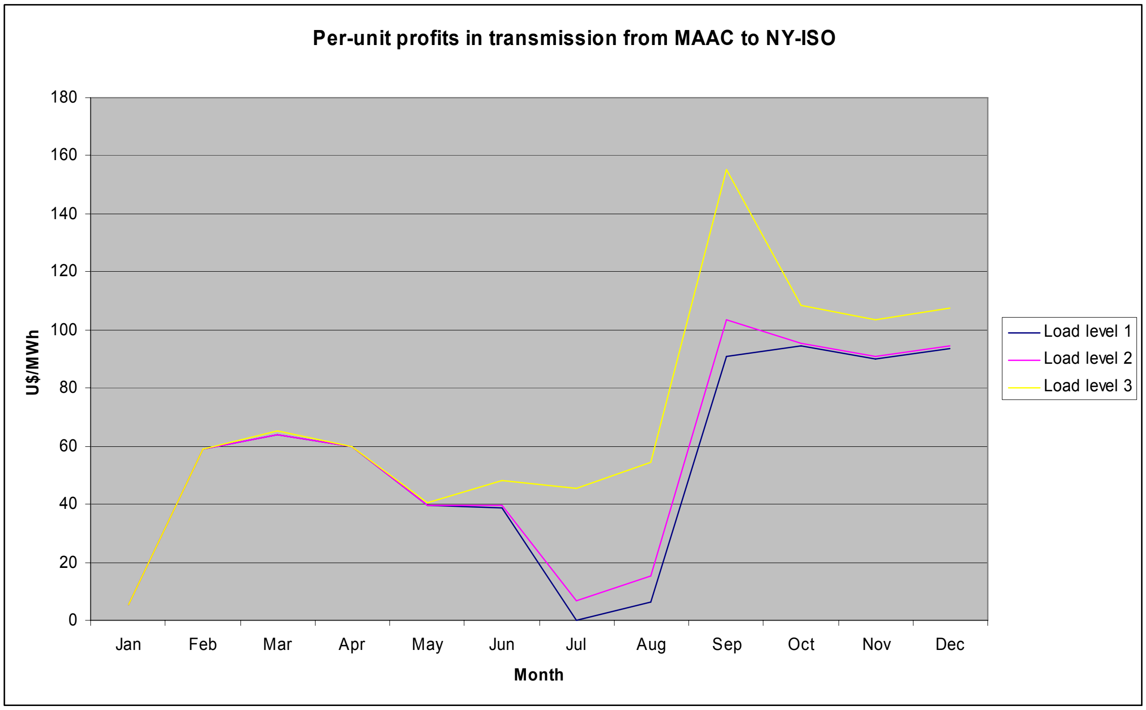

Figure 7.12. Profit per unit of flow in transmission from MAAC to NY-ISO

Although the northeast US is a summer peaking area having highest demand in the July-August time period, it is interesting to notice that Figure 7.12 indicates low congestion in that period, and maximum congestion in September. This is because during the July-August time period nodal prices in MAAC also increase because of the high demand, so the price differential in that transmission line, and therefore the congestion, decreases. The month of highest congestion (September 2005) coincides with the month immediately after Hurricane Katrina, which illustrates how the effects of the disruption in the natural gas subsystem in the Gulf Coast propagated geographically to the Northeast and also permeated to the electric subsystem.

7.3.2 Example

This section presents an example of the applicability of the model for capacity expansion assessments. This example is inspired by a 765 kV High Surge Impedance Loading (HSIL) transmission overlay projected to go from South Dakota to New Jersey in 2016. This conceptual project motivated an exploratory study by MISO [MISO, 2006]. Even though a study of this nature requires looking into the future and model uncertain conditions many years ahead, a similar scenario, but using 2005 data, is proposed in this section for illustrative purposes only.

Consider that after realizing the significant differences in nodal prices between MAPP and NY-ISO, an investor is evaluating a project to build a DC transmission line to send energy from South Dakota (MAPP) to New York (NY-ISO). Assume also that the investor is considering between a 1000 and a 2000 MW transmission line. Since there is no arc between directly connecting MAPP and NY-ISO in the NEES network model, it is necessary to add one to the network with an adequate value for capacity.

Three simulations were performed to evaluate the project:

- Case A (base case): No arc between MAPP and NY-ISO was included. This is the same case used for validation presented in Section 7.1.
- Case B: A 1000 MW transmission line between South Dakota and New York is modeled, for each time step, as 3 arcs connecting the MAPP electric transshipment node to each of the 3 nodes corresponding to the NY-ISO electric transshipment (one per each load level). These arcs have capacities equal to $1000 \cdot 24 \cdot 30 \cdot 0.5$, $1000 \cdot 24 \cdot 30 \cdot 0.4$, and $1000 \cdot 24 \cdot 30 \cdot 0.1$ (units are MWh).
- Case C: A 2000 MW transmission line between South Dakota and New York is modeled as in case B, but with the arcs having twice the capacity.

After simulating case A in CPLEX, the total operation cost was 174.5894 billion dollars. With a 1000 MW transmission line (case B) connecting MAPP and NY-ISO, the total operation cost would have been reduced by 299.5 million dollars, while for a 2000

MW transmission line (case C) the system savings would have been 513.8 million dollars. Even though the exploratory study in [MISO, 2006] does not provide any information regarding the capacity in MW of the line, it does provide some simulation results for a 2016 scenario, indicating a net $900 million dollars per year savings. Considering the differences in the simulation scenarios and the fact that the capacity of the line is not provided in the MISO study, the result provided by the NEES network model is reasonable. The change on nodal prices at different electric transshipment nodes are portrayed in Figure 7.13.

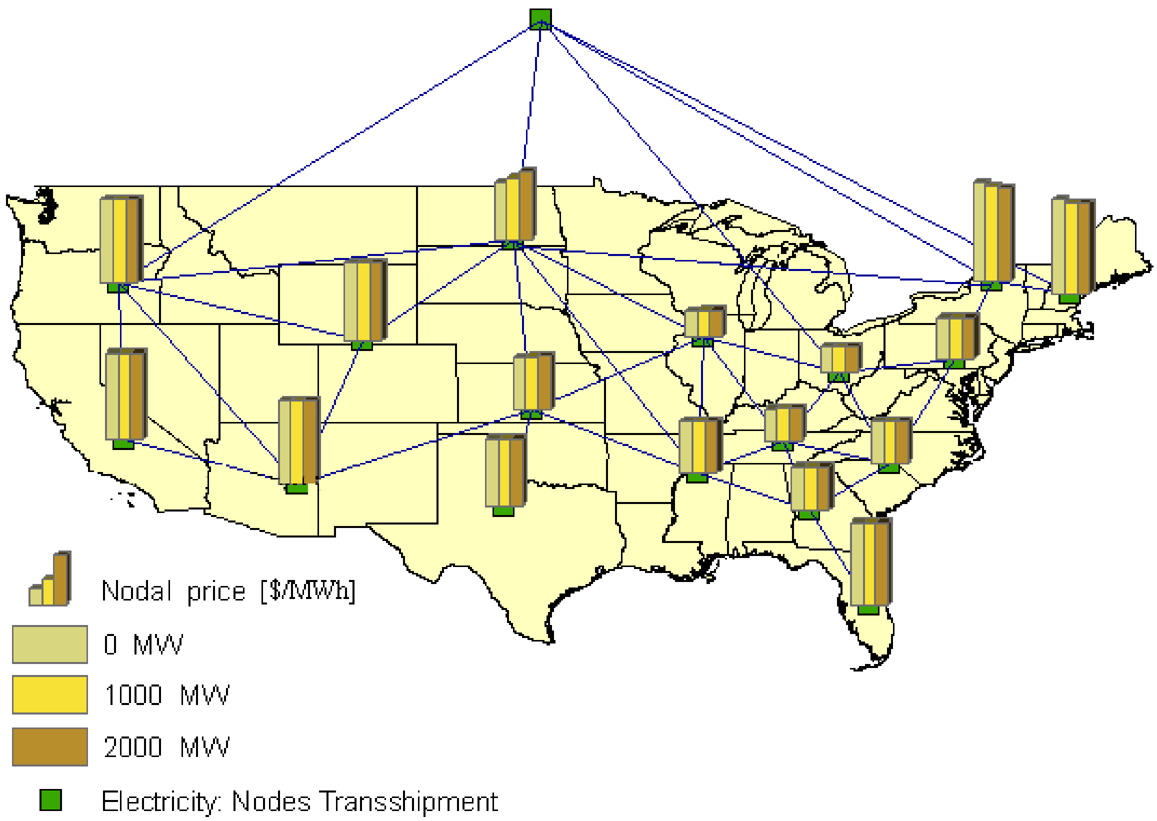

Figure 7.13. Nodal prices for the example

The nodal prices in NY-ISO and ISO-NE would clearly decrease as a result of building the transmission line, since part of the electric energy produced by the local more expensive generation would be replaced by imports coming from MAPP, and because of a reduction in the congestion in transmission lines close to NY-ISO (as it can be observed in the per-unit profits in Figure 7.14). On the other hand, the nodal prices in MAPP and its surrounding NERC regions increase, since use of more expensive generation would be required in order to supply not only the local demand but also to export energy to NY-ISO through the newly created electric transmission corridor. The conclusion is obvious: as more transportation capacity is available, nodal price differences tend to decrease.

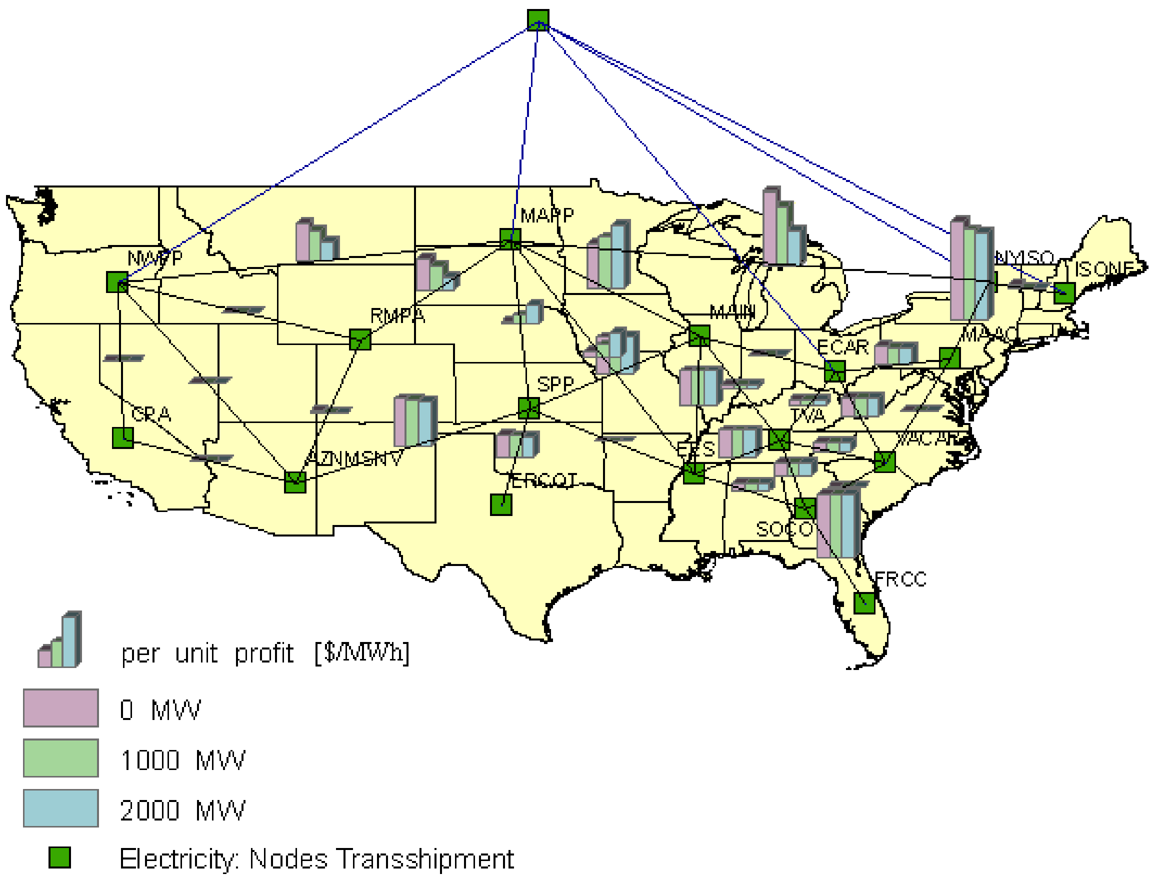

Figure 7.14. Profits per unit of flow for the example

As observed in Figure 7.14, per-unit profits (and therefore congestion) decrease in the arcs surrounding NY-ISO, since part of its demand is now supplied from MAPP and the surrounding areas do not need to send that much energy in NY-ISO direction. On the other hand, the congestion from SPP, EES, and MAIN to MAPP increased, because higher nodal prices at MAPP motivate its neighbors to send more energy into MAPP's direction. Also, it can be observed that the congestion from MAPP to NWPP and to RMPA decreased. The meaning of this is that the difference in nodal prices made more attractive to send power from MAPP to the East than sending it to the West. Thus, less flow in those arcs was necessary and congestion in those particular arcs decreased. It is interesting to observe at this point that the closer are the arcs to the facility change (in this case the transmission line between MAPP and NY-ISO), the more their per-unit profits are affected.

Even though all the previous information may be especially valuable for a centralized decision maker trying to motivate investments, it is not that relevant from the investor point of view. From the investor point of view, it is more interesting to evaluate how the different alternatives will affect his profits, in order to evaluate his project and contrast his profits with his eventual financial costs. The per-unit profit for the arc between MAPP and NY-ISO is illustrated in Figure 7.15.

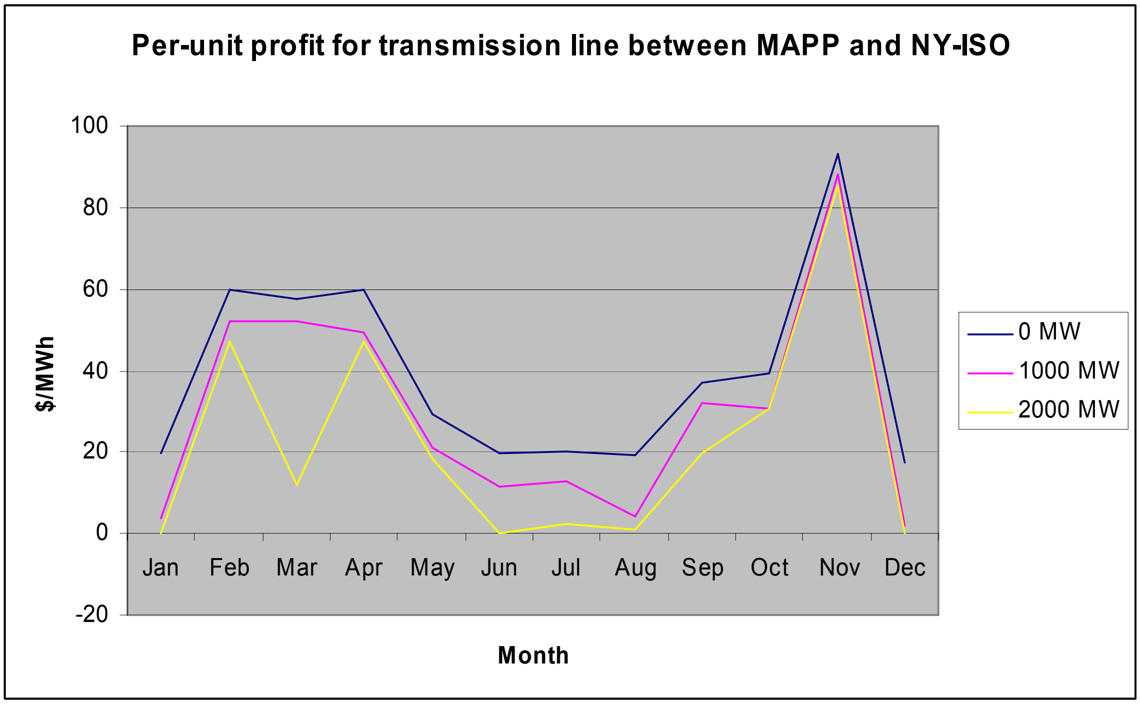

Figure 7.15. Profit per unit of flow for transmission line between MAPP and NY-ISO

From comparing the per-unit profits for the different alternatives, it is clear that the larger the capacity of the transmission line, the less is the profit. If the transmission line capacity is large enough, the profits would be driven down to 0 and the new line would not be congested at any time. As more energy flows from MAPP to NY-ISO, the closer their nodal prices will be, and the smaller will be the profit. If the profit becomes small enough, the investor may start becoming attracted to put his money in other projects that are more profitable.

The nodal price increase in MAPP as a result of the new transmission line may also motivate other types of investment. For example, the per-unit profit in the coal-fired units increased by 27.7% in average in MAPP (considering the 2000MW line). The gas-fired generation also increased in MAPP with the transmission line, which caused the nodal price of natural gas at the Central transshipment node to increase by approximately 1%.

7.4 Assessment of vulnerabilities in the NEES

The all near-minimum capacity minimal cut-sets enumeration algorithm, adapted to work on a generalized network like the NEES as explained in Section 6.4, was implemented in MATLAB. After setting a dummy source node s connected to all raw energy production nodes and a dummy sink node t connected to all the transshipment nodes, minimal cut-sets were enumerated for different values of ε. Using a value of $\varepsilon = 0.05$, one minimum capacity minimal cut-set and one near-min minimal cut-set (with a capacity less than 5% higher than the minimum capacity) were identified. Using $\varepsilon = 0.1$, another near-min minimal cut-sets was identified, and using $\varepsilon = 0.2$, another one was found. The running time in all the cases did not exceed 1 minute. The first 2 minimal cut-sets, MC1 and MC2 are enumerated below. The list of components provided for each minimal cut-set corresponds to the arcs comprising the cut-set.

Minimal Cutset 1 (MC1)
Capacity: 5040545006 MWh (equivalent)
NG imports from Canada: Western, Central, Midwest, and Northeast.
NG production: California, Other Western, Rocky Mountain, Kansas, Other Central, New Mexico, Texas, Oklahoma, Arkansas and Louisiana, Gulf of Mexico, Midwest, Northeast, Mississippi and Alabama, and Other Southeast.
Coal generation: NWPP, CPA, AZNM, RMPA, MAPP, SPP, ERCOT, MAIN, ECAR, MAAC, EES, TVA, VACAR, SOCO, FRCC, NYISO, and ISONE.

Minimal Cutset 2 (MC2)
Capacity: 5238691850 MWh (equivalent)
NG imports from Canada: Central, Midwest, and Northeast.
NG transportation from Western to Central transshipment node.
NG production: Rocky Mountain, Kansas, Other Central, New Mexico, Texas, Oklahoma, Arkansas and Louisiana, Gulf of Mexico, Midwest, Northeast, Mississippi and Alabama, and Other Southeast.
Coal generation: NWPP, CPA, AZNM, RMPA, MAPP, SPP, ERCOT, MAIN, ECAR, MAAC, EES, TVA, VACAR, SOCO, FRCC, NYISO, and ISONE.
NG generation: NWPP, CPA, and AZNM.

Because of the min-cut max-flow theorem, the capacity of MC1 corresponds to the maximum flow that can be sent from the source node *s* to the sink node *t*. MC1, the minimal cut-set of minimum capacity, comprehends all the pipelines importing natural gas from Canada, all the natural gas production, and all the coal generators in each region. That is, the reduction in capacity of any of those arcs will reduce the system capacity.

MC2, with a capacity only 3.9% higher than the capacity of MC1, is interesting in because it is more heterogeneous than MC1, in the sense that it is comprised by facilities of different kinds and, unlike MC1, some transportation arcs belong to it. This minimal cut-set comprehend arcs which interruption would interrupt part of the natural gas going from West to East.

The minimal cut-sets provide some insight into the elements that are more vulnerable in terms of availability of energy in the NEES. However, since the total demand of the system corresponds to 81.6% of the capacity of the minimal cut-set, many facilities would have to be disrupted in order for the system to be incapable to supply the demand. Thus, it seems unlikely that the NEES as a whole may have problems of supply interruption.

Therefore, the focus from now on will be in using the near-min minimal cut-set enumeration algorithm to identify conditions that may lead to a shortage of supply in a particular node. In order to do a vulnerability assessment for a given node, it is necessary to set as the sink node *t* the node of interest, which for effects of illustration will be the NY-ISO electric transshipment node. It is important to realize that by setting the NY-ISO node as the sink node, the solution of the maximum flow algorithm implicit in the near-min minimal cut-set enumeration algorithm will try to send the maximum possible flow to the sink node, independent of the individual demands of its neighbors. Thereby, the capacity of the minimal cut-set calculated in this way is an upper bound on the energy that a node is able to receive in reality. However, since NY-ISO is mainly an importer of energy, it can be expected this upper bound to be close to the actual maximum capacity.

Figure 7.16 presents the rate of use of system capacity, corresponding to the demand in the node divided by the maximum possible flow obtained by the algorithm. In July and August, for load level 3, the demand in NY-ISO gets dangerously close to the maximum possible flow, which indicates that a disruption in any of the arcs comprising the minimum capacity minimal cut-set might cause the loss of load.

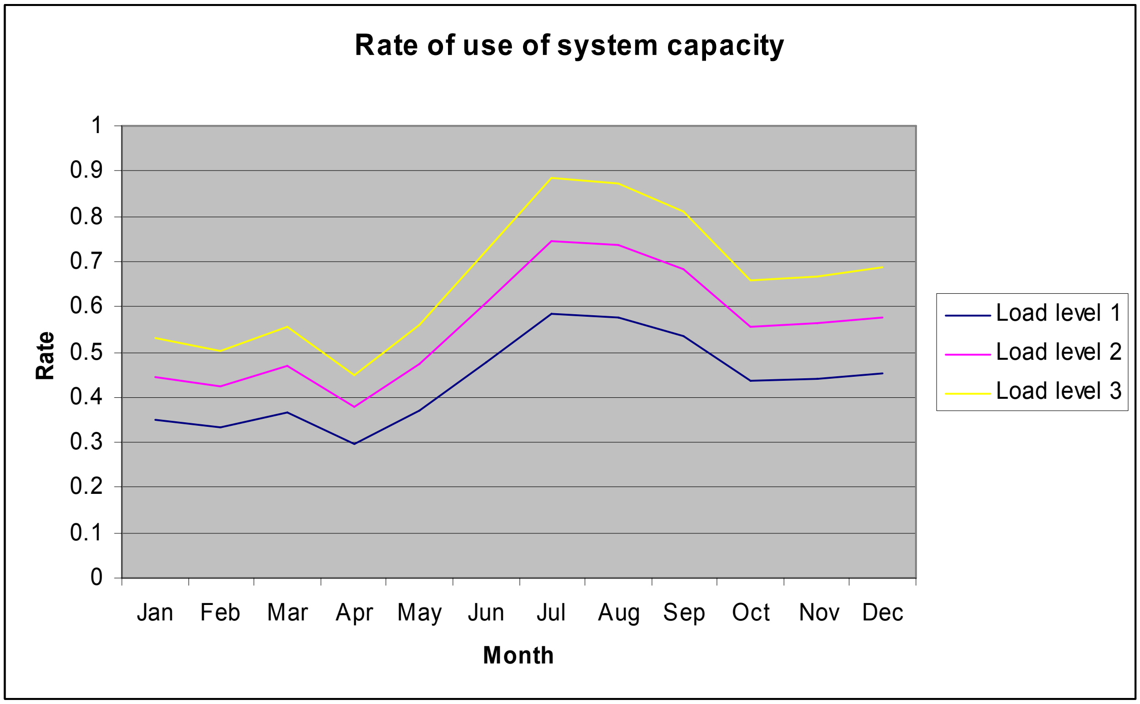

Figure 7.16. Rate of use of system capacity in NY-ISO

Note that the curve representing the rate of use of the system capacity follows very closely the actual LMP in NY-ISO presented in Figure 7.2, which suggests a relationship between nodal price and the capacity of the minimal cut-set.

8 Conclusions

The underlying hypothesis motivating this research work is that by analyzing the coal, natural gas, and electric sub-systems in an integrated analytical framework, a better assessment of the effects of disruptions and capacity expansion investments in the NEES could be achieved than by analyzing the systems separately.

Through its pages, this dissertation has sought to provide a better understanding of how the interdependencies in the system work, shed some light on how congestion, reliability, and prices are linked, facilitate the identification of alternative energy supplies, and be of assistance in the prevention of resource adequacy problems. By analyzing the three subsystems together, we have been able to obtain insight into how the different subsystems interact, and we have gained understanding in regards to how the effects of changes in the parameters of the system propagate geographically and in time. The utilization of this single integrated analytical framework enabled different kinds of analyses that would have been unattainable or impractical with the systems analyzed individually.

The NEES network model, along with the techniques derived from it, will allow the decision makers to firstly, evaluate the impact of disruptions and identify potential vulnerabilities in the NEES, and secondly, assess capacity expansion investments both in terms of their contribution to congestion relief and in terms of its potential profitability.

8.1 Specific contributions

<u>Integrated analytical framework for the coal, natural gas and electric subsystems</u>

The NEES network model incorporated the coal, natural gas, and electric subsystem, traditionally examined separately, into a single analytical framework. The application of generalized network flow concepts for modeling the energy movements in the NEES allows for a set of flexible and powerful mathematical and analytical set of tools.

Data gathering and organization

The process of gathering and organization of energy-related data to develop a realistic model, an immense task by itself, proved to be very valuable to attain a better understanding of the individual characteristics of each subsystem. Data was collected in two fronts:

- Energy infrastructure data to describe the operation of the NEES facilities during 2005 (parameters of the NEES network model, prices, and flows).
- Specific data characterizing the effects of hurricanes Katrina and Rita in the NEES (changes in parameters of the NEES network model and changes in prices and flows).

Simulations were carried out in order to validate the values of the parameters of the NEES network model derived from this data. From the comparison of simulated and actual data, the model followed the trends observed in prices and flows, and it was successful in reproducing the effects of hurricanes Katrina and Rita on energy prices.

Characterization of the impacts of hurricanes Katrina and Rita

The collection of hurricane-related data became an important part of this research. Characterization of the impacts of hurricanes Katrina and Rita in the NEES network model was also important to obtain a better understanding of the impact of disruptive events in the energy grid, to appreciate how the effects of an event propagate geographically and in time, and to study infrastructure interdependencies. Acquiring such knowledge can be helpful in order to prevent the most harmful effects of disruptions, raise awareness about infrastructure vulnerabilities, and to improve the government and industry reaction capacity in the aftermath of catastrophic events.

Model improvements to simulate changes in the network parameters

Under the effects of a major contingency, it may be the case that some of the basic assumptions of the model may be too restrictive so that they may limit the validity of the results. Four specific model improvements/adaptations were deemed necessary to properly simulate abrupt and large changes in the NEES network parameters. These improvements were tested with good results. Specifically:

- The technique of disaggregating the electric demand by load levels proved to be adequate and greatly extended the analytical capabilities of the NEES network model.
- Inclusion of elasticity in the demand: This model improvement was shown to be necessary for more accurate results when constructing hypothetical test cases. If not implemented, in the Katrina simulations the demand may have been off by almost 8%.
- Avoidance of infeasibilities: Although implemented, its use did not become necessary since the disruption cases analyzed were not large enough to cause a misbalance between energy supply and demand. However, for different testing conditions, it may become necessary.
- Storage decoupling: It allowed modeling more realistically the decision making processes following an abrupt change in the operating conditions in the energy grid. It was implemented in all the simulations.

Use of duality theory for assessments in the network

Duality theory was used to provide mathematical and analytical support to the nodal-price metrics used for assessment of reliability and congestion. Duality theory results were constantly used in the study of the impact of changes in the network parameters.

Study of changes in the network parameters

Two different types of changes in the network parameters were investigated through this work:

- Disruptive events, which were translated in the NEES network model as reductions in the capacity of one or more arcs. Hurricanes Katrina and

Rita widespread effects in the NEES became the ideal test-bed for the study of disruptive events.

- Capacity expansion projects, which were implemented in the NEES network model as increases in the capacity of one or more arcs.

Development of metrics for assessment of reliability and congestion

The assessment of reliability and congestion in the NEES was performed through the introduction and development of metrics. These metrics proved to be especially valuable for the assessment of conditions related to changes in the capacity of one or more of the facilities. In the network model, the usage of nodal prices or reduced costs for the assessment of congestion and reliability will depend on the nature of the assessment and on who is making the decisions. While the interest of a centralized decision maker will be more focused on the effects of changes in the network on energy prices at specific locations (as represented by the nodal prices), an investor interest will be more concentrated on the effects that such changes in the network will have on its profits (as represented by the reduced costs). Assessment of vulnerability in the system was performed by using a technique purely based in the capacity of the arcs. The metrics based in nodal prices were more informative than the based in capacity. While the metric based purely on capacity is too generic and difficult to interpret, the metrics based on nodal price always clearly provided the right types of signals to decision makers, and for different system locations and times.

8.2 Directions of further research

- Improve data quality and quantity: Many of the model's simplifying assumptions are necessary because of unavailability of good quality disaggregated publicly available data, and not necessarily because theoretical limitations of the modeling techniques.
- Disaggregation of the nodes by load levels proved to be especially useful to extend the analytical capabilities of the NEES network model. Further

disaggregation of other electric transshipment nodes using load levels, as more data becomes available, might be necessary to improve the accuracy of the simulations, especially in the electric subsystem.

- By using a larger number of nodes to represent more accurately the geographical diversity of the NEES, the results of the model will become more specific and more interesting to industry people. Geographic disaggregation can also be useful to include some intraregional congestion constraints that have not been incorporated in the model so far.

- Using smaller time steps would improve the accuracy in the modeling of the system dynamics.

- Pricing of transportation and transmission services are very complex issues whose complexity in the NEES network model is absorbed into a single parameter (the per-unit cost). Improving the cost model, if the necessary data becomes available, will make the results of more interest to the energy industry.

- Incorporate a behavioral dimension into the model in order to better model how decisions are actually made in the NEES.

- Include a power flow in the mathematical formulation of the electric subsystem would help modeling network limitations imposed by Kirchhoff laws.

- The assessment of capacity expansion investments in the NEES would be greatly benefited by extending the range of the model to address long term studies.

Appendix: Acronyms

AAR	Association of American Railroads
AGA	American Gas Association
ATC	Available Transfer Capability
AZNM	Arizona-New Mexico-Southern Nevada Power Area
Bcf	One billion cubic feet
Btu	British thermal unit
CO2	Carbon dioxide
CPA	California Power Area
CTRDB	Coal Transportation Rate Database
DOE	U.S. Department of Energy
ECAR	East Central Area Reliability
EES	Entergy Electric System
EIA	Energy Information Administration
EPA	U.S. Environmental Protection Agency
ERCOT	Electric Reliability Council of Texas
ES&D	Electricity Supply and Demand Database
ETS	Emission Tracking System
FASTR	FERC Automated System for Tariff Retrieval
FERC	Federal Energy Regulatory Commission
FRCC	Florida Reliability Coordinating Council
GIS	Geographic Information System
GWh	Gigawatt-hour (one thousand megawatt-hours)

INGAA	Interstate Natural Gas Association of America
ISO	Independent System Operator
ISONE	ISO New England
kW	Kilowatt (one thousand watts)
kWh	Kilowatt-hour (one thousand watt-hour)
LMP	Locational Marginal Price
MAAC	Mid-Atlantic Area Council
MAIN	Mid-America Interconnected Network
MAPP	Mid-Continental Area Power Pool
Mcf	One thousand cubic feet
MMcf	One million cubic feet
MMS	Minerals Management Service
MRO	Midwest Reliability Organization
MW	Megawatt (one million watts)
MWh	Megawatt-hour (one million watt-hour)
NEES	National Electric Energy System
NERC	North American Electric Reliability Council
NOx	Nitrogen oxides
NPCC	Northeast Power Coordinating Council
NWPP	Northwest Power Pool
NYISO	New York Independent System Operator
RF	Reliability First
RMPA	Rocky Mountain Power Area
RTO	Regional Transmission Organization

SERC	Southeastern Electric Reliability Council
SO2	Sulfur dioxide
SOCO	Southern Company
SPP	Southwest Power Pool
TTC	Total Transfer Capability
TVA	Tennessee Valley Authority
VACAR	Virginia-Carolinas Area
WECC	Western Electricity Coordinating Council

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